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Advancements and Challenges in Hydrological Modelling

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Abstract: This paper reviews recent advancements and applications of hydrological models for effective water resource management. Hydrological models have evolved significantly over the past four decades, enhancing their ability to simulate complex hydrological processes with improved spatial and temporal precision. Advances such as the integration of high-resolution data, adaptive grid resolutions, and data assimilation techniques like the Ensemble Kalman Filter have improved model accuracy, especially in flood prediction and catchment-scale hydrological assessments. However, challenges persist, including high computational demands, data scarcity in certain regions, and limitations in modelling nonlinear flow dynamics in diverse environments. The review underscores the need for continued research, particularly in machine learning and remote sensing, to refine model capabilities. These advancements will be crucial for addressing the impacts of climate change on water resources and supporting sustainable watershed management strategies.
Keywords: Hydrological models, types of models, model applications, model limitations.

I. INTRODUCTION

This study presents a comprehensive literature review to understand and highlight the significance of water balance studies conducted across the world and its drawbacks. Estimating water yield and water balance within a river catchment is essential for determining water stocks across different components of the hydrologic cycle and understanding fluxes between them (Zhang et al., 2024). This method is vital for sustainable water resource management at the watershed level. Evaluating water resources at scales smaller than the watershed allows for effective regional watershed management. Knowing the volume of water within different hydrologic cycle components aids in (a) sustainably managing water resources and preventing overuse and pollution, (b) assessing climate change impacts on water availability, (c) analysing how land-use changes affect water resources, (d) identifying recharge zones, and (e) supporting rainwater harvesting efforts (Sidle, 2021). This foundational knowledge supports effective planning and resource management by addressing the dynamic interactions within the hydrological cycle at local and regional levels. Hydrological modelling provides an effective approach for consistently analysing the long-term hydrologic patterns at a catchment or basin scale and conducting various behavioural studies (Su et al., 2024). These hydrologic components are represented mathematically and known as hydrological models. Hydrological models can simulate the physical processes governing the movement of water, sediment, chemicals, and nutrients within catchments and help quantify the impacts of human activities on these dynamics (Anand et al., 2018). The need to accurately determine runoff volumes from specific events has been a primary driver behind the development of rainfall-runoff models, which are essential for predicting and managing water flow in response to rainfall. Now a days, it is difficult to address a water resource issue without the application of a hydrologic model (Sidle, 2021). Hydrologic models have become essential tools for solving a wide range of ecological and water resource challenges, from the design and development stages to planning and managing available water resources effectively. Their versatility and evolving precision have made them central to sustainable water resource management. A wide range of simulation models exists, and selecting the most suitable model involves balancing data needs with implementation costs. The value of a hydrologic model lies in its ability, when appropriately selected and calibrated, to extract the most accurate insights from available data, providing reliable information essential for sustainable water resource management.

Hydrological models have become increasingly sophisticated with advancement in computational power and the enhanced availability of spatial and temporal data from satellite technology (Sidle, 2021). The integration of remote sensing data has revolutionized hydrological modelling by providing large-scale, high-resolution data on key parameters such as rainfall, land use, soil moisture, and snow cover. Remote sensing technologies, such as satellites and drones, offer continuous spatial and temporal coverage, making them invaluable for monitoring and modelling hydrological processes, especially in areas with limited ground-based observations. Remote sensing data are particularly useful in physically-based models, which require detailed information about the spatial variability of hydrological processes (Naha et al., 2016).

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For example, satellite-derived precipitation data can be used to improve rainfall estimates in remote or ungauged catchments. Despite the advances in remote sensing, challenges remain in integrating these data into hydrological models. One of the main issues is the resolution of the data, which may not always match the scale of the model (Chen et al., 2021). Additionally, uncertainties in remote sensing measurements, such as errors in estimating precipitation or soil moisture, can affect model accuracy. Therefore, further research is needed to improve data assimilation techniques and develop methods for validating remote sensing data against ground-based observations (Naha et al., 2016). This review work has been grouped into different sections based on the classification of hydrological modelling approaches, their applications and advances, and challenges and limitations.

II. HYDROLOGICAL MODELLING APPROACHES

A hydrological model is a simplified representation of real-world hydrological processes, utilized to predict water behaviour and manage water resources effectively. These models can be categorized based on their structure and the spatial processes they simulate, ranging from small-scale physical models to complex mathematical and computer simulations (Chen et al., 2021). Hydrological models are primarily classified into empirical/statistical, conceptual, and physical types (Devia et al., 2015; Sidle, 2021). Empirical models depend solely on observed data, without considering underlying hydrological processes, making them data-driven. Conceptual models, in contrast, incorporate key hydrological processes and parameters, while physical models use mathematical equations to represent real-world phenomena in an idealized form. Models are further categorized by spatial representation—lumped, semi-distributed, or distributed—and by their operational nature as either deterministic or stochastic (Devia et al., 2015).

A. Empirical Models

Empirical models are observation-oriented, or data-driven models, rely entirely on information from existing datasets without directly incorporating the features or physical processes of the hydrological system. These models, often called “black box” models, use mathematical relationships derived from historical input and output data rather than actual catchment processes. As a result, they work within specific data boundaries and may not apply outside these limits. The unit hydrograph is a classic example of this approach, as it establishes the relationship between rainfall and runoff without accounting for internal catchment dynamics. Statistically based models, such as regression and correlation techniques, aim to define functional relationships between inputs and outputs. Machine learning methods, like artificial neural networks (ANNs) and fuzzy regression, are increasingly used in hydrological modelling to capture complex patterns in data-driven models.

Additionally, empirical models like the Curve Number method, ANNs, and regression techniques rely entirely on data and are typically employed in two key applications: (1) modelling rainfall–runoff relationships from existing data, ANNs; (Srinivasulu and Jain, 2006) and (2) estimating runoff in ungauged catchments by transferring empirical parameters from nearby gauged catchments with similar hydrological characteristics (Blöschl, 2006). Recent advancements have enabled these models to incorporate some aspects of catchment characteristics (Asadi et al., 2019; Blöschl, 2006), enhancing their utility in data-scarce or ungauged regions.

However, these models often oversimplify precipitation distribution and struggle to capture complex physical processes within a catchment, which can introduce errors. They tend to perform well in predicting downstream discharge but usually lack detailed spatial information about within-catchment processes (Sitterson et al., 2018). Despite improvements in representing non-linear rainfall–runoff responses (Sivakumar et al., 2001), empirical models remain limited for predicting outcomes in complex catchments with diverse land cover and geomorphology, and they often cannot accurately reflect the impacts of land-use changes (Sidle, 2021).

B. Conceptual Models

Conceptual hydrological models connect various water cycle components within a catchment area using straightforward, functional algorithms that simulate the main hydrologic processes. These algorithms include parameters that may not correspond directly to physical measurements and thus require calibration to align model outputs with observed data hence considered as “grey box”. Conceptual models often use multiple “reservoirs” arranged in series, representing the flow and storage of water through the atmosphere, surface, and subsurface layers, including soil and groundwater systems (Wagener et al., 2010).

The Stanford Watershed Model (SWM), developed by (Crawford and Linsley, 1966), paved a way for numerous conceptual hydrological models and platforms. Recently, TOPMODEL, a semi-distributed conceptual model introduced by (Beven and Kirkby, 1979), has become widely used in hydrological studies. Its flexible time-step structure, added in later developments, addressed some of the earlier limitations in fixed time-stepping seen in similar models, making it adaptable to a broader range of applications (Clark and Kavetski, 2010).

The lumped structure of this model effectively represents hydrological pathways, providing simplicity in calculations. The studies by (Phuong et al., 2018; Yokoo et al., 2001) have shown that this type of models often performs better than more complex models. However, these models do not account for the detailed catchment characteristics and spatial variability.

(Wagener et al., 2010) showed that calibrating conceptual hydrological models usually requires extensive meteorological and hydrological data to assess how sensitive different parameters are to changes in the system. Calibration is typically done by adjusting model parameters to fit historical data, allowing the model outputs to match observed system behaviour. However, this process can complicate analysis, especially when inferring the impacts of land-use changes (Beven and O'Connell, 1982). For highly parameterized conceptual models or complex process-based models, sensitivity analysis is essential. This step, often involving a comparison of various approaches, helps optimize model performance and identify any unnecessary parameters before starting the modelling process (Song et al., 2015).

C. Physically-based models

Physically-based models, also known as process-based or mechanistic models, are designed to represent the fundamental physical processes governing hydrological systems within a catchment. Unlike empirical or conceptual models, which rely on simplified relationships or aggregated representations, physical models use mathematical equations to simulate real-world hydrological processes, including the conservation of mass, energy, and momentum. These models rely on state variables, measurable quantities that vary over time and space, such as water depth, soil moisture, and flow velocity to describe water movement through the system. Physically-based models can integrate parameters with direct physical interpretations, making it possible to simulate a wide range of hydrological conditions and predict behaviour under diverse scenarios. This method often uses finite difference equations to model water movement between surface and subsurface layers, ensuring that critical interactions, such as infiltration, percolation, and surface runoff, are accounted in detail (Abbot et al., 1986). These models are highly adaptable and, when properly calibrated, can provide detailed insights into the complex interactions within hydrological systems, offering a robust framework for scientific and practical applications in water resource management.

These models typically require extensive data inputs describing catchment characteristics such as initial soil moisture, topography, river network dimensions, and topology. Because of these detailed requirements, physically-based models often demand substantial computational resources and detailed field data, making them complex to implement and calibrate (Beven and O'Connell, 1982). Additionally, they also face criticism due to their high data demands, nonlinear behaviour, and issues related to scale compatibility (Beven, 2012; Grayson et al., 1992).

Recent advances in remote sensing and computational power have solved the problem of extensive data inputs to physically-based models and aided to simulate processes across scales and provided information even beyond the physical boundaries of the data inputs, which is invaluable for understanding responses to external influences like climate change or land-use change (Blöschl, 2006; Sidle et al., 2017). Some popular examples of physically-based models include MIKE-SHE, HEC-HMS and NOAH. These models can effectively simulate the exchange of water and energy balances between plant-land-atmosphere interaction in catchment involving sediments, nutrients and chemicals.

III. MODEL APPLICATIONS AND ADVANCES

(Thornthwaite and Mather, 1957) pioneered the water balance method to help assess water needs for irrigation and other related requirements. Expanding on this approach, (Vasiliades et al., 2011) utilized a water balance-derived drought index to evaluate drought patterns in Greece's Pinios River Basin. Similarly, (Imteaz et al., 2012) used a water balance model to determine the ideal size for rainwater tanks for domestic use in southwest Nigeria. In another application, (Zeleke and Wade, 2012) estimated evapotranspiration by combining soil water balance data with weather and crop information. (Campos et al., 2016) also applied this method by integrating water balance modelling with evapotranspiration data to gauge soil water availability in vineyards. (Plagnes et al., 2017) used water balance modelling to guide management strategies for a uranium mill effluent system in northern Saskatchewan, Canada. (Xia et al., 2022) incorporated irrigation processes into land surface-hydrological models to improve the accuracy of evapotranspiration estimates and highlights the redistribution of water resources due to irrigation in Yangtze River Basin, China. (Jasrotia et al., 2009) demonstrated that using Thornthwaite and Mather's models, enhanced by remote sensing and GIS, effectively detects moisture surplus and deficit within watersheds. (Loucks et al., 2017) further highlighted the value of water balance modelling for planning, designing, and operating water systems, emphasizing its importance in effective water resource management.

(Abbaspour et al., 2015) developed a comprehensive hydrological model of Europe using the SWAT (Soil and Water Assessment Tool) model, allowing them to measure various hydrologic components at a sub-basin scale on a monthly basis. (Visakh et al., 2019) also applied the SWAT model to simulate long-term water balance components across river basins in Eastern India's delta districts, providing insight into the regional hydrology. (Siderius et al., 2013) combined four hydrological models named: VIC, JULES, LPJmL, and SWAT, with regional climate models to assess snowmelt contributions to streamflow in the Ganges Basin on both seasonal and annual scales. (Singh et al., 1999) used the MIKE SHE model to compute water balance in a small catchment, aiming to design an irrigation plan. (Rahim et al., 2012) also employed MIKE SHE to simulate water balance and various hydrological components for the Paya Indah Wetlands watershed. (Su et al., 2024) employed two models (VIC and NOAH-MP) for improving the runoff simulation through calibration in the Western United States. (Meles et al., 2024) coupled Hydrus-1D and KINEROS2 model to simulate overland and subsurface flow at catchment scale. This coupled modelling framework effectively addressed the complexities of hydrological processes by utilizing a dynamic time-stepping approach and boundary condition switching, which enhances the simulation of water movement across different domains.

Recently, data assimilation (DA) techniques are used in hydrological modelling as they merge observational data with process-based models, enhancing prediction accuracy and reducing uncertainty. Methods like the Ensemble Kalman Filter (EnKF) and advanced deep learning approaches are commonly used to handle hydrological system complexities. EnKF, for example, has shown effectiveness in updating model states and parameters, especially in snow-dominated regions, where adjusting hyperparameters plays a crucial role in improving forecast accuracy (Sabzipour et al., 2023). (Wang et al., 2024) incorporated soil moisture and leaf area index data into farmland hydrological models to significantly improve the simulation of water and carbon fluxes, with dual-factor assimilation outperforming single-factor approaches. (Zhang et al., 2024) have applied an innovative deep learning methods to address non-linear hydrological relationships, enhancing both computational efficiency and model precision. These advancements underscore the versatility and value of DA techniques in hydrological sciences, demonstrating their capacity to address a wide range of challenges in modelling and forecasting (Castelli, 2023).

Another data assimilation technique Direct Insertion (D.I.) is used in hydrological modelling to improve prediction accuracy by directly incorporating observational data into model states. This approach is particularly effective for indirect observations, like snow cover area and soil moisture, where it has sometimes outperformed techniques such as EnKF in certain applications (Naha et al., 2016). D.I enables real-time updates using satellite-derived data, making it valuable in dynamic environments with varying spatial and temporal conditions (Castelli, 2023; Pathiraja et al., 2016). Its effectiveness is highlighted by its ability to reduce uncertainties in model parameters and enhance the representation of processes like snowmelt runoff, which is crucial for improved water resource management (Naha et al., 2016). Recent advancements have introduced hybrid models, which integrate different approaches like machine learning or artificial intelligence with traditional hydrological models to enhance flexibility and accuracy in hydrological simulations to understand the complex interactions within a catchment (Wang et al., 2021).

IV. CHALLENGES AND LIMITATIONS

Although hydrological models have advanced significantly in recent decades, several challenges remain. One of the primary issues is the uncertainty associated with model predictions. Uncertainties arise from various sources, including errors in input data, limitations in the model structure, and the inherent variability of hydrological processes (Devia et al., 2015). For example, rainfall is one of the most critical inputs in hydrological models, yet it is notoriously difficult to measure accurately due to spatial and temporal variability. Similarly, the heterogeneity of soil properties (Yang et al., 2018) and land use can introduce uncertainties into models that simulate infiltration and runoff processes (Anand et al., 2018).

Another challenge is the scaling issue. Hydrological processes operate at different spatial and temporal scales, from small-scale infiltration events to large-scale river basin dynamics. Capturing these processes across scales is difficult, particularly in physically-based models, which require detailed data for each spatial unit (Beven, 2012). The choice of scale also affects the model's computational requirements, with finer-resolution models demanding more processing power and memory.

Calibration and validation are other areas of concern in hydrological modelling. Many models require calibration to ensure that their predictions match observed data. However, calibration is often a trial-and-error process, and it can be difficult to achieve good results in ungauged basins where no historical data are available (Wagener et al., 2010). Validation, which involves testing the model's performance on independent datasets, is equally challenging, especially when data are scarce or incomplete.

The river routing models, that defines how the water will flow in a river within a catchment, are closely integrated with specific land-surface hydrological models.

This restricts to have a discharge at a coarser resolution ~ 50 km. However, there are some open models also available to route runoff at variable grid resolution, but may oversimplify the kinematic or diffusive wave equations, leading to inaccuracies in specific areas (Shaad, 2018). High-resolution schemes require substantial data inputs, including detailed terrain, river network data, and calibration datasets. This can make them resource-intensive, limiting accessibility and feasibility for regions with limited data.

V. CONCLUSIONS

In conclusion, hydrological and river-routing models have become indispensable tools for understanding, predicting, and managing water resources. Over the past four decades, the field has seen considerable advancements driven by increased computational power, the availability of high-resolution spatial and temporal data, and the integration of complex physical processes into models. Modern hydrological models, with their ability to capture dynamic interactions between surface water, groundwater, and atmospheric variables, are now more capable than ever of representing complex hydrological systems across various scales. Models such as MIKE SHE, VIC and NOAH demonstrate these advances by integrating variable flow velocities, detailed topographic data, and dynamic wave equations, enhancing their accuracy in floodplain and watershed modelling. Additionally, the development of river-routing schemes also faces limitations. The high demand for extensive datasets and computational resources can restrict their application in data-scarce regions and makes real-time usage challenging. Moreover, while models have become more sophisticated, capturing intricate hydrological behaviours, they still struggle with nonlinear flow dynamics in complex environments, such as floodplains or areas with substantial subsurface flow. Scale dependency remains another challenge, as translating global models to local scales without losing accuracy or increasing computational burden is an ongoing difficulty. Moreover, continued innovation in data assimilation, machine learning, and high-resolution remote sensing holds promise for addressing some of these challenges. Combining these advancements with the adaptive capabilities of open-source platforms could make hydrological models and river-routing models more accessible, flexible, and accurate, even in data-limited regions. As the impacts of climate change and urbanization on hydrological systems intensify, the importance of further developing these models for effective water management will only grow. By enhancing model precision and reducing uncertainties, hydrological and river-routing models will remain central to water resource planning, disaster mitigation, and sustainable development efforts worldwide.

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1) Vikrant Maurya: Conceptualization, Methodology, Formal Analysis, Writing, Visualization. Manika Gupta: Conceptualization, Methodology, Supervision, Writing – review & editing.

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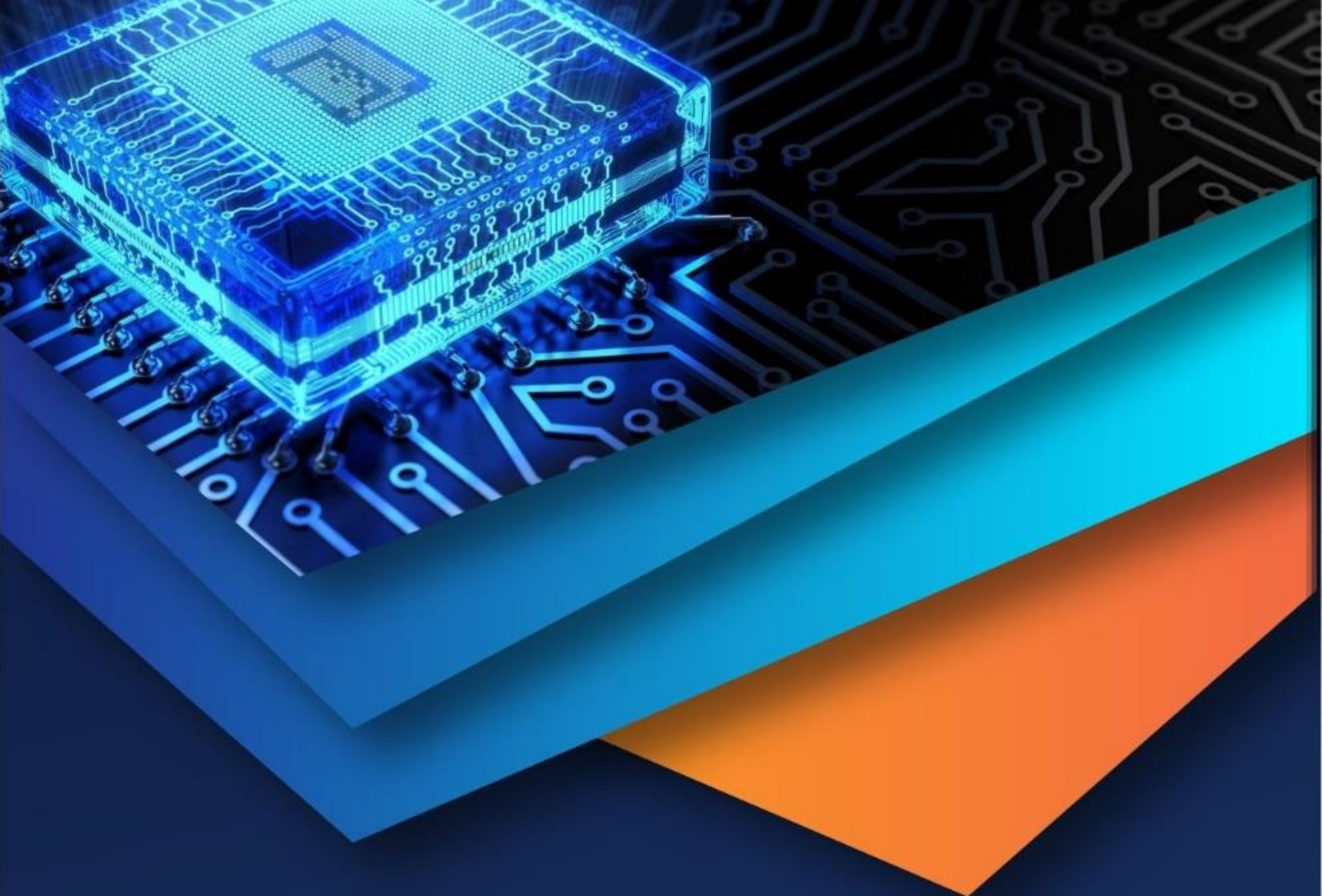

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