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# Integrated Watershed Management In A Data- Scarce Region

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## *Abstract*

*Integrated watershed management (IWM) is critical for ensuring sustainable water resource use, particularly in data-scarce regions where limited hydrological information hinders effective planning and decision-making. This study proposes a comprehensive framework for IWM tailored to such environments, leveraging machine learning techniques to reconstruct incomplete streamflow datasets. Using the completed data, a flow duration curve (FDC) is developed to characterize the watershed's flow regime. Statistical analyses are then applied to assess water availability and variability across temporal and spatial scales. In parallel, a stakeholder mapping process is conducted to ensure inclusive decision-making, enabling local communities, policymakers, and other relevant actors to participate in strategy development, validation, and implementation. The proposed framework also includes a structured approach for monitoring and evaluating the effectiveness of implemented strategies, ensuring adaptive management over time. This integrative approach aims to bridge data gaps while fostering resilient and participatory watershed governance.*

***Keywords:*** *watershed, data-scarce regions, machine learning, water availability, stakeholder mapping*

## INTRODUCTION

Global changes including climate change, urbanization, population growth, socioeconomic change, and evolving energy needs have put unprecedented pressure on water resources systems[1]. The Integrated Watershed Management (IWM) approach is essential for increasing water availability through various interventions. According to[2], watershed management is defined as the process of establishing and implementing plans, developing strategies, and initiatives to maintain and enhance the functions of a watershed that offer the values, goods, and services beneficial to the community affected by conditions within a watershed boundary.

Sustainable management of water resources requires a long series of streamflow data [3]. Streamflow data plays a crucial role in understanding the hydrological functioning of watersheds. The availability of complete quality streamflow data of sufficiently long duration is essential for characterizing the flow characteristics, estimating the occurrence of extreme events such as high or low flows, and rectifying problems like landslides, droughts, and even floods [4]. Poorly gauged river basins, low density of hydrological gauging stations, breakdown and lack of gauging equipment, vandalization of gauging equipment, inadequate funding for the sector, inaccessible sites, etc., cause a lack of adequate hydrological data which presents a significant challenge to sustainable water resources planning, design, and management in developing countries. This has resulted in short-length or non-continuous records, making collected data unsuitable for long-term planning [5].

The drainage area ratio method is one of the simplest methods available for predicting streamflow at ungauged locations. However, it may not always be effective in various possible real-world scenarios [6]. When requesting streamflow values at an ungauged site the use of drainage area ratio (DAR) is the most common and appealing since it requires no additional information other than the streamflow at an index site and the drainage areas of the index and ungauged sites, making it the easiest possible method that one could consider [7]. Many researchers have addressed the issue of predicting FDCs at ungauged or partially gauged locations through regional regression e.g., [29], [30], [31], [32], [33] as well as geostatistical interpolation [13]. Several scholars e.g., [30], [35], [36] developed spatial nonlinear interpolation methods. [16]introduced a methodology that involves using the copula function. Additionally, a method to extend and/or fill in daily flow time series at a site using monthly FDCs of the target site itself was proposed [15]. The monthly FDCs must be recorded during a donor period or retrieved using different methods such as (1) regionalization of FDCs based on available observed records from several neighboring gauges [17] or (2) conversion of FDCs calculated from monthly data into 1 d FDCs [15]. The use of machine learning algorithms in imputing hydrological data has gained considerable interest as an effective strategy for addressing issues related to missing data. Machine learning algorithms provide the potential to acquire intricate patterns and correlations within observed data, hence allowing for more accurate imputation of missing values in hydrological series. By proficiently capturing the temporal, geographical, and contextual interdependencies inherent in hydrological data, machine learning algorithms augment the accuracy of imputation. Employing these algorithms for imputation enhances data integrity, leading to advancements in hydrological modelling, resource management, and decision-making processes. This results in more comprehensive and dependable datasets, hence enabling more accurate and insightful analyses [18].

In a recent study, [19] introduced a method that presents a user-friendly strategy for using a recurrent neural network (RNN) model to retrieve missing daily flow data. The primary limitation in this context is the vanishing gradient, which occurs when RNN encounters a limitation in its ability to propagate significant gradient information from the output layers to the input layers. To address the issue, the modeling and imputation tasks in innovative research integrate RNN variants, namely Gated Recurrent Unit (GRU) and Long Short-Term Memory (LSTM), which have demonstrated effectiveness in overcoming the limitation [20], [21], [22], [23]. Other relevant studies include the Graph Neural Network (GNN) based approach to basin-scale river network learning by [24], highlighting the importance of physics-based connectivity and data fusion techniques.

Currently, many data-driven models are available ranging from simple models to models that require considerable computing power[25]. Physically based hydrological models can only capture a simplified representation of the physical processes governing streamflow, whereas the data-driven models can provide more accurate predictions [26], primarily due to better possibilities for modeling non-linear relationships [27]. [28]concluded that a missing time-series data interpolation method based on a combination of random forest (RF) and a generative adversarial interpolation network (GAIN) performs better in data filling. Studies have revealed the superiority of RFR over other ML algorithms and traditional statistical methods in streamflow prediction[29], especially in regions with intricate hydrological processes and limited data availability[30], [31].

Random Forest (RF) is a kind of machine learning algorithm, that has an excellent ability when dealing with complex nonlinear relationships between variables and can minimize overfitting problems, simple operations, and powerful functions. It is an ensemble tree-based algorithm that selects predictor variables at each split node of an independent tree and aggregates all the trees for prediction. Each regression tree is created by using a subset of observations and variables, focusing on minimizing a loss function [32]. [33] successfully utilized Random Forest Machine Learning (RFML) to predict hydrographs in snowmelt-driven mountainous watersheds. RFML has become popular in the remote sensing and hydrology communities mainly because of its higher accuracy in streamflow predictions and flood risk management, which have traditionally been challenging with traditional methods. According to[34], the extensive use of machine learning tools is expected to accelerate the development of water resource management strategies over the next decade.

The dynamic change in meteorological and hydrological parameters is crucial for assessing water availability, developing management options, and making informed decisions[35]. A flow duration curve (FDC) is used to characterize the regime of the hydrological watershed[36]. It is usually derived from historical field records and is an effective, simple, and powerful tool for analyzing the flow characteristics of a river basin[37]. The FDC analysis method examines the magnitude and frequency of historical flow data over a defined time frame, offering a comprehensive overview of ecohydrological processes within a basin. FDC's applications in water resources engineering, planning, and management are well-established[38].

Determining the impact of variations in meteorological conditions on the hydrology of a river across two distinct periods can be quite difficult when relying solely on long-term streamflow hydrographs. However, FDC analysis offers a valuable approach to determining changes in the magnitude and frequency of streamflow values under these circumstances. Researchers globally have extensively used rainfall-runoff models to analyze land use and climate impact streamflow trends that subsequently inform water resource and land-use management strategies. Despite their widespread use, these models have limitations and frequently indicate non-significant changes in streamflow, peak flows, and low flows in response to altered watershed characteristics and climate change, raising concerns about their reliability [39], [40], [41].

The FDC's long-standing history and its reliance on observational records in water resource enginering remain a robust method for addressing water-related problems such as supply for large irrigation projects, hydropower generation, environmental flow requirements for habitat management, and the effects of land use and climate changes[42], [43]. It uses non-parametric quantile estimation techniques as an alternative method for calculating the magnitude and frequency of the entire range of daily streamflow[44].

It is evident that watershed management has evolved to a more holistic resource management approach. Technological advances have significantly contributed to enhancing this approach. The presentation of tools to assess water availability and the evaluation of integrated watershed management represent an important synthesis of knowledge for scientists, stakeholders, resource managers, and government entities. This study can contribute to developing innovative approaches and practical solutions for sustainable watershed management. This study can be used to improve agencies' management strategies within watersheds of concern. By following the steps outlined for developing watershed management strategies, incorporating a random forest model, flow duration curve, stakeholder input, and gleaning insights from the related studies presented, future watershed management can be enhanced regardless of the circumstances and location.

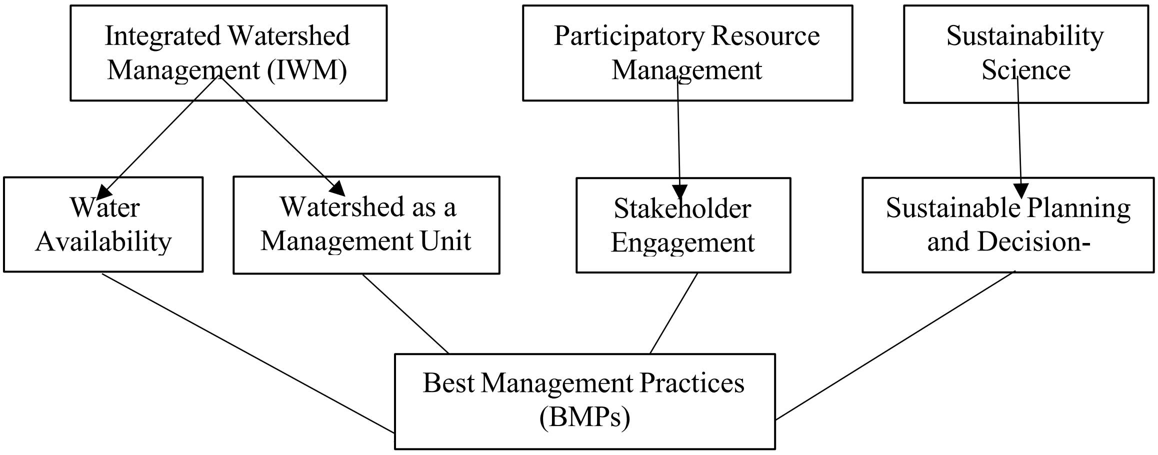

**Figure 1.** Theoretical Framework

## Conceptual Framework

The study's conceptual model is shown in the form of a paradigm in Figure 2. It utilizes the input, the throughput, and the output approach.

The INPUT of the study consisted of 10-year mean daily discharge measurements and drainage area of the basin.

The THROUGHPUT covers the different processes involved in determining Integrated Watershed Management strategies to control or increase water availability, FDC generation employing RF regression, water availability assessment, and statistical analysis.

The OUTPUT covers the Integrated Watershed Management Framework based on water availability assessment in a data-scarce region.

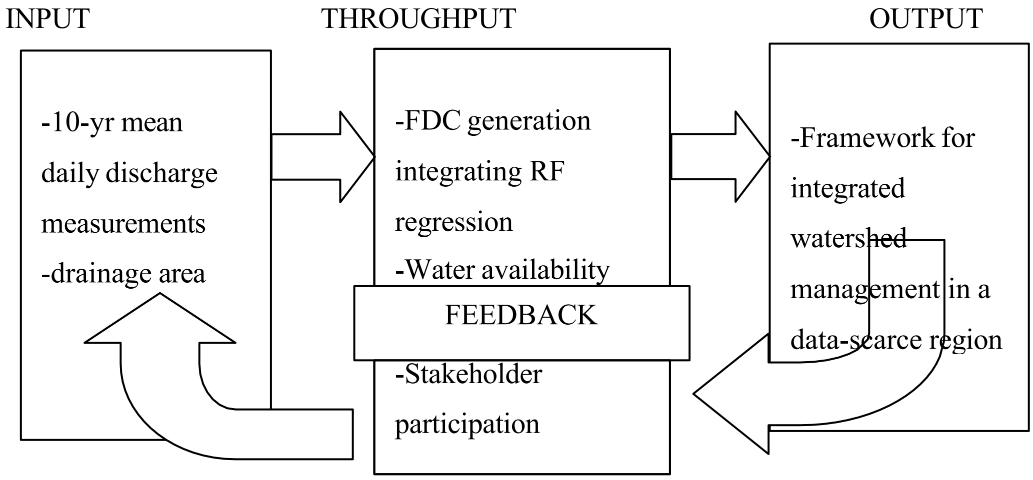

**Figure 2.** Conceptual Framework.

## METHODOLOGY

Prior to the development of watershed management strategies, it is essential to carry out a hydrological or water resources assessment to evaluate water availability. Conducting such an assessment helps ensure the sustainability of the management strategies. The utilization of observed streamflow data from hydrometric stations has been the benchmark for monitoring streamflow and assessing water resources. However, the necessary instrumentation and infrastructure are often expensive and limited to a few key stations within a catchment. The data acquired from other areas of interest within the catchment are often derived from nearby hydrometric stations leading to estimates of discharge amounts that carry inherent spatial uncertainties. Having more precise streamflow data would enhance water resources planning and management decisions, including those that involve water supply, irrigation, and flood control.

Machine learning approaches are now widely applied in the field of hydrology. Machine learning approaches have been utilized to predict flows ranging from next-day flows for example, [55], [56], to next-month flowsfor example, [57], [58], droughts for example, [59], and sub-annual floods for example, [60]. Although machine learning approaches are commonly used, only limited studies have been completed in which machine learning approaches are employed to predict flow metrics at ungauged locations for example, [61], [62], [63]. Using only the RF approach, [51] comprehensively evaluated the flow regime using more than 600 flow metrics across the conterminous United States.

This study has six stages: (1) data collection and preprocessing employing a random forest model to predict the missing daily streamflow data; (2) development of Flow Duration Curve (FDC); (3) water availability assessment; (4) statistical analysis; (5) evaluation of Integrated Watershed Management strategies based on water availability assessment; (6) validation of identified IWM strategies using stakeholder engagement. The flowchart of the present study is presented in Figure 3.

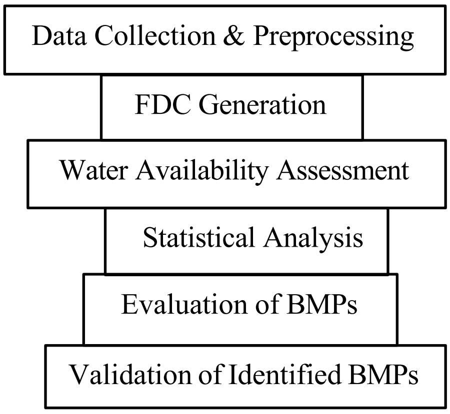

**Figure 3.** The Research Paradigm.

## RESULTS

Framework for IWM based on water availability

Figure 4 shows the iterative process in developing an IWM plan based on water availability in a data scarce watershed. (1) collection of available streamflow data; (2) imputation of missing data using random forest; (3) characterization of the river's flow regime; (4) water availability assessment; (5) experts' consultations; (6) stakeholders identification; (7) validation and setting up of the target and plan; (8) implementation of the plan; and (9) evaluation of management success and failures, reassessment of the objectives, and adjustments of the plan to improve management success.

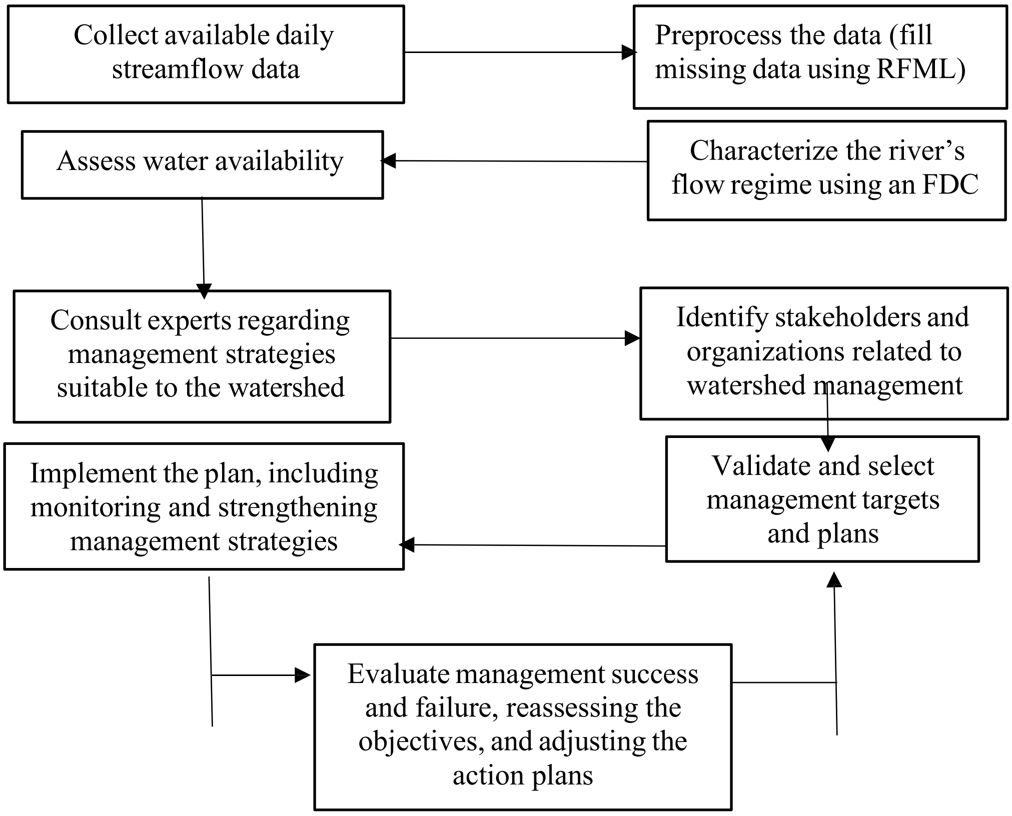

**Figure 4.** Framework for developing an IWM plan based on water availability in a data scarce watershed.

## CONCLUSIONS

It is recommended to integrate machine learning models—particularly Random Forest regression— to impute missing streamflow data and improve the accuracy of hydrological assessments conducted by local and national water agencies. Further studies could explore the use of other ML techniques like Gradient Boosting or Long Short-Term Memory (LSTM) networks, to compare model performance. Additionally, it is recommended to facilitate workshops for various stakeholders to enhance their understanding of watershed management, clarify their needs and priorities- ultimately leading to more effective watershed management. Overall, watershed management can be improved by integrating predictive tools with stakeholder engagement, ensuring data-based insights and community accepted practices are effectively implemented.

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