ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26mar073

A Hybrid Remote Sensing and Statistical Modelling Framework for River Water-Quality Forecasting During Extreme Hydrologic Events

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Publication Date: 2026/03/03

Abstract: Extreme hydrologic events such as floods and intense rainfall significantly disrupt river water quality by accelerating sediment transport, nutrient loading, and pollutant dispersion, creating major challenges for environmental monitoring and forecasting. This study presents a hybrid remote sensing and statistical modelling framework designed to improve river water-quality prediction during extreme hydrologic disturbances. Multispectral satellite data from Sentinel-2 MSI and Landsat-8 OLI were processed to derive water-quality indicators including turbidity, chlorophyll-a, and Total Suspended Matter (TSM), while ground-based hydrologic observations and meteorological datasets provided complementary temporal information. Statistical forecasting models, including Multiple Linear Regression (MLR), ARIMA/SARIMA, and Generalized Additive Models (GAM), were integrated within a data fusion architecture to combine spatial and temporal predictors. Model performance was evaluated using RMSE, MAE, coefficient of determination, and Nash–Sutcliffe Efficiency metrics under event-based validation conditions. Results demonstrate that the hybrid framework substantially outperforms standalone remote sensing and statistical approaches, reducing prediction error by more than 25% and improving forecasting reliability during flood peaks. The system successfully detected pollution pulses, captured spatial heterogeneity across the river basin, and maintained stable prediction accuracy during pre-event, peak, and post-event phases. Findings highlight the value of satellite observations for monitoring inaccessible regions and confirm that integrated modelling enhances early-warning capability for water-quality degradation. The study provides a scalable methodological foundation for operational environmental monitoring systems, supporting water utilities, environmental protection agencies, and disaster-response planning in river basins increasingly affected by climate-driven hydrologic extremes.

Keywords: *Hybrid Modelling; Remote Sensing; River Water Quality Forecasting; Extreme Hydrologic Events; Environmental Monitoring Systems.*

How to Cite: Itohaosa Isibor; Otugene Victor Bamigwojo; Lawrence Enyejo; Gamaliel Ibuola Olola (2026) A Hybrid Remote Sensing and Statistical Modelling Framework for River Water-Quality Forecasting During Extreme Hydrologic Events. *International Journal of Innovative Science and Research Technology,* 11(3), 1-25. https://doi.org/10.38124/ijisrt/26mar073

I. INTRODUCTION

➢ *Background and Research Context*

Extreme hydrologic events have become increasingly frequent and intense across many regions of the world, largely driven by climate variability, land-use transformation, and anthropogenic environmental pressures. Floods, extreme rainfall episodes, and storm surges significantly alter watershed hydrodynamics, accelerating runoff processes and reshaping riverine systems within short temporal scales (IPCC, 2021; Kundzewicz et al., 2019). These events disrupt the natural equilibrium of river ecosystems by mobilizing sediments, transporting pollutants, and modifying physicochemical water properties, thereby posing substantial risks to ecological health and human water security (Blöschl et al., 2020; Mishra & Coulibaly, 2021). As hydrologic extremes intensify, forecasting water quality during such disturbances has become a critical scientific and management priority.

One of the most immediate consequences of extreme hydrologic events is the rapid deterioration of river water

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26mar073

quality parameters. Flood-induced erosion and surface runoff increase turbidity levels due to elevated concentrations of suspended particles entering river channels (Dogliotti et al., 2015). Suspended sediment concentration (SSC) often rises sharply during high-flow conditions, influencing light penetration, aquatic productivity, and sediment deposition dynamics (Vanmaercke et al., 2021). Simultaneously, dissolved oxygen (DO) levels may decline as organic matter loads increase and microbial decomposition accelerates, creating hypoxic conditions harmful to aquatic organisms (Wang et al., 2018). Nutrient loading, particularly nitrogen and phosphorus transported from agricultural and urban landscapes, intensifies during storm events and can trigger eutrophication and harmful algal blooms downstream (Tong et al., 2017). In addition, biological contamination, including pathogen transport from wastewater overflow and surface runoff, becomes more prevalent during floods, increasing public health risks associated with water use (Sterk et al., 2016).

Despite the importance of monitoring these parameters, conventional in-situ water-quality monitoring networks face significant operational limitations during extreme hydrologic events. Fixed monitoring stations often provide sparse spatial coverage and may become inaccessible, damaged, or nonfunctional during floods and severe storms (Horsburgh et al., 2019). Moreover, manual sampling approaches lack the temporal resolution required to capture rapid water-quality fluctuations that occur during peak discharge periods. These constraints create critical data gaps precisely when accurate environmental information is most needed for emergency response and water-resource management (Kirschbaum et al., 2020).

Recent advances in satellite remote sensing have transformed large-scale environmental monitoring by enabling continuous, synoptic observation of surface water systems. Multispectral and hyperspectral satellite platforms such as Landsat, MODIS, and Sentinel missions provide repeated observations capable of estimating water-quality indicators across extensive geographic areas (Pahlevan et al., 2020). Remote sensing techniques allow indirect retrieval of turbidity, chlorophyll concentration, and suspended sediments through spectral reflectance analysis, offering an effective alternative where ground measurements are limited or unavailable (Dekker et al., 2018). Importantly, satellite-based monitoring enables rapid assessment of water-quality changes during extreme hydrologic events, supporting near–real-time environmental surveillance and forecasting applications (Tyler et al., 2016).

The integration of remote sensing observations with statistical modelling approaches therefore represents a promising pathway toward improving river water-quality forecasting under extreme conditions. By combining spatially continuous satellite data with hydrologic and meteorological predictors, hybrid frameworks can overcome limitations of traditional monitoring systems while enhancing predictive capability and decision support for water-resource management.

- *Problem Statement*

Accurate forecasting of river water quality during extreme hydrologic events remains a persistent scientific and operational challenge due to limitations in observation systems and modelling integration. One of the primary difficulties arises from temporal gaps in ground-based monitoring during floods, extreme rainfall, and storm-driven hydrologic disturbances. Conventional in-situ monitoring stations typically operate at fixed sampling intervals and are often unable to capture rapid fluctuations in water-quality conditions occurring over short timescales. During extreme events, monitoring infrastructure may become submerged, damaged, or inaccessible, resulting in missing datasets precisely when high-frequency observations are most critical for environmental assessment and emergency decision-making (Horsburgh et al., 2019; Kirschbaum et al., 2020). Consequently, the absence of continuous temporal records reduces the reliability of predictive models and limits the ability to detect sudden pollutant pulses or sediment surges associated with peak discharge periods (Blöschl et al., 2020).

In addition to temporal limitations, river systems exhibit strong spatial heterogeneity in water-quality responses during hydrologic extremes. Variations in watershed characteristics, land use, topography, and tributary inflows cause localized differences in sediment transport, nutrient loading, and contaminant dispersion. Floodwaters often mobilize pollutants unevenly across catchments, producing complex spatial gradients that cannot be adequately represented using sparse monitoring stations (Vanmaercke et al., 2021). These heterogeneous responses complicate efforts to generalize water-quality behaviour across river basins and introduce uncertainty into forecasting frameworks that rely solely on point-based observations (Mishra & Coulibaly, 2021). As a result, environmental managers lack spatially continuous information required for targeted intervention and risk assessment.

Satellite remote sensing offers significant potential to address observational gaps by providing synoptic spatial coverage; however, integrating satellite-derived measurements with predictive statistical models remains technically challenging. Remote sensing data are often affected by atmospheric interference, cloud cover, sensor limitations, and differences in temporal resolution compared with hydrological datasets (Pahlevan et al., 2020). Furthermore, translating spectral reflectance into quantitative water-quality parameters requires calibration and validation processes that introduce additional uncertainties (Dekker et al., 2018). Statistical forecasting models, on the other hand, typically depend on structured time-series inputs, making the fusion of irregular satellite observations with continuous hydrologic records complex (Reichstein et al., 2019). Differences in data scales, formats, and noise characteristics hinder seamless integration and reduce model robustness during extreme conditions.

These combined challenges highlight the absence of a unified framework capable of bridging temporal observation gaps, representing spatial variability, and effectively

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26mar073

integrating remote sensing datasets with statistical forecasting approaches. Addressing this methodological disconnect is essential for improving river water-quality prediction accuracy and supporting proactive water-resource management during extreme hydrologic events.

➢ *Research Aim and Objectives*

The increasing occurrence of extreme hydrologic disturbances has intensified the need for advanced analytical frameworks capable of forecasting river water quality with improved accuracy and timeliness. Traditional monitoring and modelling approaches often operate independently, with remote sensing providing spatial observations and statistical models delivering temporal predictions. However, the absence of an integrated framework limits the ability to fully exploit complementary strengths between Earth observation technologies and predictive analytics. This study therefore aims to develop a hybrid framework that combines multisource remote sensing datasets with statistical modelling techniques to enhance river water-quality forecasting during extreme hydrologic events.

The primary aim of this research is to design and implement an integrated predictive system capable of capturing both spatial variability and temporal dynamics of water-quality parameters under rapidly changing hydrologic conditions. By leveraging satellite-derived environmental indicators alongside hydro-meteorological datasets, the proposed framework seeks to improve forecasting reliability during floods, extreme rainfall episodes, and related disturbances. The framework is intended not only to generate accurate predictions but also to strengthen early-warning capabilities for environmental managers, water utilities, and disaster-response agencies. Enhanced predictive performance can support proactive interventions, reduce ecological risks, and improve decision-making during periods when conventional monitoring systems are constrained.

To achieve this aim, the study pursues several interrelated objectives. First, water-quality indicators will be extracted from multispectral satellite imagery through spectral analysis techniques capable of estimating parameters such as turbidity, suspended sediment concentration, and related optical properties. These satellite-derived variables provide spatially continuous information that complements point-based ground observations. Second, statistical forecasting models will be developed using hydro-meteorological variables, including precipitation intensity, river discharge, and temperature, to capture temporal patterns and event-driven fluctuations in water quality. These models will establish quantitative relationships between environmental drivers and observed water-quality responses.

Third, the research will integrate remote sensing outputs and statistical predictors into a unified hybrid predictive architecture. This integration involves temporal alignment, feature fusion, and model calibration processes designed to harmonize datasets with differing spatial and temporal resolutions. The hybrid structure is expected to overcome limitations associated with standalone approaches by combining observational coverage with predictive analytical capability. Finally, the performance of the developed framework will be evaluated during documented extreme hydrologic events using established validation metrics to assess forecasting accuracy, robustness, and operational reliability.

Collectively, these objectives establish a systematic pathway toward developing a scalable and adaptive water-quality forecasting framework capable of supporting real-time environmental monitoring and early-warning systems under extreme hydrologic conditions.

➢ *Research Questions*

The growing complexity of river water-quality dynamics during extreme hydrologic events necessitates targeted scientific inquiry into the effectiveness of emerging monitoring and modelling approaches. This study is guided by a set of research questions designed to evaluate the predictive capability of satellite observations, the suitability of statistical forecasting techniques, and the advantages of integrating multiple analytical methodologies within a hybrid framework. These questions provide a structured foundation for assessing whether combining remote sensing and statistical modelling can significantly improve water-quality forecasting under rapidly changing environmental conditions.

The first research question examines whether satellite-derived indicators can reliably predict water-quality degradation during extreme hydrologic disturbances. Remote sensing platforms capture variations in spectral reflectance associated with suspended sediments, organic matter, and algal concentrations, which are closely linked to key water-quality parameters. However, uncertainties related to atmospheric interference, sensor resolution, and indirect parameter estimation raise important concerns regarding reliability. This question therefore investigates the extent to which remotely sensed indices can serve as dependable proxies for in-situ measurements, particularly during periods of high turbidity and dynamic hydrological change.

The second research question focuses on identifying which statistical modelling approaches most effectively capture event-driven variability in river systems. Extreme hydrologic events introduce nonlinear responses, abrupt regime shifts, and short-term fluctuations that challenge traditional modelling techniques. Statistical models differ in their ability to represent temporal dependencies, accommodate nonstationary behaviour, and incorporate hydro-meteorological drivers. Evaluating alternative modelling strategies allows the study to determine which approaches best represent rapid water-quality transitions associated with floods and extreme rainfall events.

The third research question evaluates whether hybridization, defined as the integration of satellite observations with statistical forecasting models, provides measurable improvements over standalone methods. Remote

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26mar073

sensing offers extensive spatial coverage but limited temporal continuity, whereas statistical models provide temporal forecasting capacity but rely heavily on observational inputs. By combining these complementary strengths, the study investigates whether hybrid frameworks can reduce prediction error, enhance forecasting lead time, and improve early-warning performance compared with independent modelling or observation-based approaches.

Together, these research questions establish the analytical direction of the study, enabling systematic evaluation of data sources, modelling techniques, and integration strategies required to advance river water-quality forecasting during extreme hydrologic events.

➢ *Significance of the Study*

The significance of this study lies in its contribution to advancing predictive environmental monitoring and decision-support systems for river basins exposed to extreme hydrologic events. As floods, intense rainfall, and hydrologic disturbances increasingly threaten water resources, the ability to forecast water-quality conditions becomes essential for safeguarding ecosystems, infrastructure, and public health. By developing a hybrid framework that integrates remote sensing observations with statistical modelling, this research provides a scientifically grounded approach for improving situational awareness and operational response during environmental emergencies.

One important contribution of the study is its support for disaster-response water management. Extreme hydrologic events often trigger sudden deterioration in water quality through sediment mobilization, pollutant transport, and microbial contamination. Emergency managers and water authorities require timely information to implement mitigation measures such as temporary water-treatment adjustments, contamination advisories, or controlled reservoir releases. The proposed forecasting framework enables earlier detection of water-quality degradation, allowing decision-makers to transition from reactive responses toward proactive risk management strategies. Improved forecasting capability can reduce environmental damage, minimize disruptions to water supply systems, and enhance coordination among disaster-response agencies.

The study also enables near–real-time environmental monitoring by leveraging satellite remote sensing data combined with predictive statistical analysis. Conventional monitoring networks frequently suffer from limited spatial coverage and delayed reporting, particularly during extreme events when field access is restricted. The integration of multispectral satellite imagery provides continuous spatial observations across entire river basins, while statistical models translate these observations into forward-looking predictions. This combined approach supports dynamic monitoring systems capable of delivering timely insights into evolving water-quality conditions, thereby improving environmental surveillance and resource management efficiency.

Furthermore, the research enhances resilience planning for river basins by providing a scalable analytical framework adaptable to diverse geographic and climatic contexts. Long-term resilience depends on understanding how water-quality systems respond to extreme hydrologic stressors and incorporating that knowledge into planning and policy development. The hybrid forecasting framework can assist planners in identifying vulnerable regions, evaluating risk scenarios, and designing adaptive management strategies that strengthen basin-wide resilience. By improving predictive understanding of water-quality responses, the study contributes to sustainable river management practices and supports broader climate adaptation efforts.

Overall, the study bridges observational technologies and predictive analytics to deliver practical and scientific value, advancing both operational water management and long-term environmental resilience in the face of increasing hydrologic extremes.

II. LITERATURE REVIEW

➢ *River Water Quality Dynamics During Extreme Hydrologic Events*

Extreme hydrologic events significantly influence river water-quality dynamics by altering physical transport processes, chemical balances, and ecological interactions within aquatic systems. Floods and intense rainfall events modify watershed hydrology through rapid increases in surface runoff, channel flow velocity, and sediment mobilization, leading to substantial short-term and long-term impacts on riverine environments. Understanding these processes is essential for predicting water-quality responses and developing effective monitoring and management strategies under extreme climatic conditions.

One of the most prominent mechanisms affecting water quality during hydrologic extremes is flood-driven sediment transport. High discharge conditions increase erosive forces across riverbanks, agricultural lands, and upstream catchments, mobilizing large quantities of suspended sediments into river channels. Elevated sediment loads increase turbidity, reduce light penetration, and disrupt aquatic habitats, thereby influencing biological productivity and ecosystem stability (Walling & Collins, 2016). Sediment transport during floods is often nonlinear, with peak sediment concentrations occurring during rising hydrograph stages due to rapid erosion and sediment flushing processes (Vanmaercke et al., 2021). These dynamics complicate predictive modelling because sediment responses vary depending on watershed characteristics, antecedent soil moisture, and land-use patterns (Blöschl et al., 2020).

Extreme hydrologic events also accelerate nutrient mobilization and pollutant runoff across landscapes. Heavy rainfall enhances overland flow, transporting fertilizers, organic matter, pesticides, and urban contaminants into river systems. Nitrogen and phosphorus load typically increase during storm events as agricultural soils and urban surfaces release accumulated nutrients into drainage networks

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26mar073

(Sharpley et al., 2018). This influx of nutrients can stimulate eutrophication processes downstream, contributing to algal blooms and oxygen depletion in receiving waters (Tong et al., 2017). In addition, floodwaters frequently transport industrial pollutants and untreated wastewater due to infrastructure overflow or failure, further degrading water quality and posing risks to human health and aquatic ecosystems (Olds et al., 2018).

Another critical aspect of river water-quality dynamics during extreme hydrologic events is event-based variability in water chemistry. Rapid hydrologic changes alter physicochemical parameters such as dissolved oxygen, temperature, conductivity, and pH, often within short time intervals. Increased organic matter inputs during floods intensify microbial respiration, which can reduce dissolved oxygen concentrations and create hypoxic conditions (Wang et al., 2018). Furthermore, mixing between surface runoff and baseflow sources produces complex chemical signatures that vary spatially and temporally throughout an event (Kaushal et al., 2020). These episodic fluctuations challenge traditional monitoring approaches that rely on periodic sampling, as critical water-quality transformations may occur between measurement intervals.

Overall, river water quality during extreme hydrologic events is governed by interconnected processes involving sediment transport, nutrient fluxes, pollutant mobilization, and rapid chemical variability. The episodic and highly dynamic nature of these processes underscores the need for integrated monitoring and forecasting approaches capable of capturing both spatial complexity and temporal evolution during hydrologic disturbances.

River water quality during extreme hydrologic events is governed by complex interactions among hydrological forcing, sediment transport processes, and anthropogenic environmental pressures. Rapid rainfall and flood conditions accelerate watershed runoff, mobilizing sediments, nutrients, and contaminants that significantly alter physicochemical water characteristics within short temporal windows. Contemporary environmental systems research emphasizes that dynamic environmental responses increasingly require integrated analytical frameworks capable of linking physical processes with data-driven predictive modelling (Adewale, 2026).

High-energy flow conditions enhance erosion across catchment surfaces, transporting suspended particles into river channels and increasing turbidity levels. These sediment influxes reduce light penetration, disrupt aquatic productivity, and modify ecological balance. Data-driven modelling approaches demonstrate that nonlinear environmental responses often emerge during disturbance events, requiring analytical systems capable of representing rapidly changing system states rather than static environmental assumptions (Adewale, 2025a).

In addition to sediment transport, extreme hydrologic conditions intensify nutrient and pollutant migration across agricultural and urban landscapes. Runoff mobilizes accumulated surface contaminants, leading to episodic degradation of water quality. Lifecycle-oriented environmental assessment frameworks highlight how environmental disturbances propagate through interconnected systems, reinforcing the importance of integrated monitoring strategies that capture both immediate hydrologic impacts and downstream ecological consequences (Adewale, 2025b).

➤ *Remote Sensing Applications in Water Quality Monitoring*

Remote sensing technologies have become essential tools for monitoring water quality across rivers, lakes, and coastal environments, particularly where traditional field-based measurements are limited in spatial and temporal coverage. Optical satellite sensors enable continuous observation of surface water characteristics by measuring spectral reflectance properties associated with suspended particles, phytoplankton concentrations, and dissolved substances. Advances in Earth observation missions have significantly improved the ability to assess water-quality dynamics at regional and global scales, supporting environmental monitoring and predictive modelling applications (Pahlevan et al., 2020).

Among the most widely used platforms for water-quality monitoring are multispectral optical sensors such as Landsat, Sentinel-2, and the Moderate Resolution Imaging Spectroradiometer (MODIS). Landsat missions provide long-term historical datasets with moderate spatial resolution, making them valuable for detecting temporal trends in turbidity and sediment transport (Dekker et al., 2018). Sentinel-2 imagery offers higher spatial and spectral resolution, including red-edge bands that enhance sensitivity to suspended sediments and chlorophyll concentrations in inland waters (Vanhellemont & Ruddick, 2016). MODIS, although coarser in spatial resolution, provides high temporal frequency observations that allow continuous monitoring of large river systems and rapid environmental changes during hydrologic events (Tyler et al., 2016). Together, these sensors enable multiscale analysis of water-quality variability.

Spectral indices derived from satellite reflectance data play a central role in translating optical measurements into quantitative water-quality indicators. The Normalized Difference Turbidity Index (NDTI) is commonly used to estimate turbidity levels by exploiting differences between red and green spectral bands sensitive to suspended particles. Studies have shown that NDTI effectively captures sediment plume dynamics and turbidity fluctuations in rivers and estuaries under varying hydrologic conditions (Lacaux et al., 2007). Similarly, chlorophyll-a estimation relies on spectral relationships between blue and green wavelengths, allowing remote detection of phytoplankton biomass and algal bloom development (Gitelson et al., 2008). These methods provide insight into biological productivity and nutrient enrichment processes that influence water quality.

Another important application of remote sensing involves the retrieval of Total Suspended Matter (TSM),

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26mar073

which represents the concentration of organic and inorganic particles within water bodies. Algorithms linking reflectance in red and near-infrared wavelengths to suspended sediment concentration have demonstrated strong correlations with field observations, enabling spatial mapping of sediment transport patterns (Nechad et al., 2010). TSM retrieval is particularly useful during flood events, when sediment loads increase rapidly and conventional monitoring becomes challenging. By integrating spectral indices and retrieval algorithms, remote sensing provides a cost-effective and scalable approach for assessing water-quality conditions across large and inaccessible regions.

Recent advances in data-driven material and systems analytics demonstrate that high-resolution observational datasets can significantly enhance environmental monitoring when integrated with computational modeling frameworks (Adewale, 2025c). Multispectral satellite platforms generate repeatable measurements capable of detecting variations in suspended sediments, organic matter concentrations, and biological activity within water bodies.

- *Statistical and Data-Driven Water Quality Forecasting Models*

Statistical and data-driven modelling approaches play a critical role in forecasting river water quality by capturing relationships between environmental drivers and observed physicochemical responses. These methods provide quantitative tools for predicting variations in water-quality parameters such as turbidity, dissolved oxygen, nutrient concentrations, and suspended sediments, particularly under dynamic hydrologic conditions. Over time, forecasting techniques have evolved from traditional regression-based models toward hybrid analytical frameworks that integrate statistical inference with machine learning and hydrologic data assimilation.

Regression models represent one of the earliest and most widely applied statistical approaches in water-quality prediction. Linear and multiple regression techniques establish empirical relationships between dependent water-quality variables and explanatory predictors such as rainfall, discharge, temperature, and land-use indicators. These models are valued for their interpretability and relatively low computational requirements, making them suitable for baseline forecasting and environmental assessment (Helsel et al., 2020). However, regression approaches often struggle to represent nonlinear interactions and rapid fluctuations associated with extreme hydrologic events, which limits their predictive performance in highly dynamic river systems.

To address temporal dependencies in environmental data, time-series approaches such as Autoregressive Integrated Moving Average (ARIMA) and Seasonal ARIMA (SARIMA) models have been widely employed. These methods analyse autocorrelation structures within historical datasets to forecast future water-quality conditions based on past observations. ARIMA models are particularly effective in capturing short-term temporal trends, while SARIMA extends this capability by accounting for seasonal variability commonly observed in hydrologic and ecological processes (Box et al., 2015). Time-series models have demonstrated strong performance in predicting parameters such as dissolved oxygen and nutrient concentrations, although their reliance on stationary assumptions can reduce accuracy during abrupt hydrologic disturbances.

Recent advances have introduced machine learning statistical hybrids that combine classical statistical modelling with data-driven learning algorithms. Techniques such as artificial neural networks, support vector regression, and ensemble learning approaches enhance forecasting capability by modelling nonlinear relationships and complex interactions among environmental variables (Reichstein et al., 2019). Hybrid models often integrate statistical preprocessing with machine learning prediction stages, allowing improved generalization and reduced forecasting error compared with standalone methods. These approaches are particularly effective when large, multivariate datasets are available from remote sensing and hydrologic monitoring systems.

An important advancement in modern forecasting frameworks is the integration of hydrologic covariates into statistical models. Variables such as precipitation intensity, river discharge, watershed runoff, and temperature significantly influence pollutant transport and water chemistry dynamics. Incorporating these covariates improves model sensitivity to hydrologic forcing and enhances predictive reliability during extreme events (Shmueli, 2010). Hydrologic covariate integration allows models to link physical watershed processes with statistical prediction mechanisms, thereby bridging empirical analysis and process-based understanding.

Data-driven environmental modeling parallels developments in multivariate analytical chemistry and complex-system optimization, where integrated datasets enable improved prediction reliability across heterogeneous conditions (Animashaun et al., 2024a). Such approaches demonstrate that combining multiple predictors enhances model robustness compared with single-variable forecasting methods.

- *Hybrid Environmental Modelling Frameworks*

Hybrid environmental modelling frameworks have emerged as powerful analytical approaches for addressing the complexity of environmental systems characterized by spatial variability, temporal uncertainty, and multidimensional data sources. Traditional single-source modeling techniques often struggle to capture the dynamic interactions between hydrologic, climatic, and ecological processes. Hybrid frameworks overcome these limitations by integrating diverse datasets and analytical methods, enabling more robust environmental forecasting and decision support. In water-quality prediction studies, hybrid models increasingly combine remote sensing observations, statistical analytics, and hydrologic information to improve predictive accuracy and system reliability.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26mar073

A central component of hybrid environmental modelling is the application of data fusion techniques, which integrate datasets originating from multiple sensors, temporal scales, and observational platforms. Data fusion enables the combination of satellite imagery, in-situ monitoring records, and meteorological datasets into a unified analytical structure. These techniques reduce uncertainty by leveraging complementary strengths among datasets, such as the spatial continuity of remote sensing and the accuracy of ground-based measurements (Hall & Llinas, 2017). Fusion approaches may involve feature-level integration, model-level coupling, or decision-level aggregation, each designed to enhance environmental interpretation and forecasting performance. In hydrologic applications, data fusion has proven effective in improving estimates of environmental variables where observational gaps exist.

Another important aspect of hybrid frameworks is the coupling of remote sensing data with predictive analytics. Satellite-derived environmental indicators provide extensive spatial coverage, while predictive models offer temporal forecasting capability. Integrating these components allows environmental systems to be monitored continuously while simultaneously generating forward-looking predictions. Machine learning and statistical models can incorporate remotely sensed variables as predictors, enabling the identification of nonlinear relationships between environmental drivers and water-quality responses (Reichstein et al., 2019). This coupling enhances forecasting capability during extreme hydrologic events, when rapid environmental changes require both spatial awareness and predictive insight.

Hybrid environmental modelling also supports the development of multi-source environmental forecasting systems designed to operate across scales and data domains. These systems combine hydrologic models, meteorological forecasts, satellite observations, and statistical algorithms within unified platforms capable of real-time or near–real-time prediction. Multi-source frameworks improve resilience by reducing reliance on any single dataset and enabling adaptive responses to changing environmental conditions (Liu et al., 2018). Such systems are increasingly applied in flood forecasting, water-quality monitoring, and ecosystem management, where integrated data streams provide comprehensive situational awareness.

Overall, hybrid environmental modelling frameworks represent a significant advancement in environmental forecasting methodologies. Through data fusion, integration of remote sensing with predictive analytics, and multi-source system development, these frameworks provide scalable solutions capable of addressing complex environmental challenges. Their application in river water-quality forecasting offers a pathway toward improved prediction accuracy, enhanced monitoring coverage, and more effective environmental management during extreme hydrologic events.

➢ *Research Gaps*

Despite substantial advancements in water-quality monitoring and environmental modelling, several critical research gaps remain in the application of hybrid frameworks for forecasting river water quality during extreme hydrologic events. Existing studies have demonstrated the individual strengths of remote sensing technologies and statistical modelling approaches; however, their integration under rapidly changing hydrologic conditions remains limited. Many current models are developed and validated under normal or moderately variable flow regimes, which reduces their effectiveness during floods and extreme rainfall events characterized by abrupt environmental transitions (Mishra & Coulibaly, 2021). Extreme events introduce nonlinear system responses, increased uncertainty, and data discontinuities that are not adequately addressed by conventional modelling frameworks.

One major gap involves the limited integration of monitoring and predictive systems specifically designed for extreme-event conditions. Remote sensing studies often focus on retrospective analysis rather than real-time forecasting, while statistical models frequently rely on continuous in-situ datasets that may become unavailable during disasters. As a result, existing approaches rarely provide unified analytical systems capable of simultaneously capturing spatial variability and temporal dynamics during hydrologic extremes (Pahlevan et al., 2020). The lack of coordinated integration between observational technologies and predictive analytics restricts the development of reliable early-warning mechanisms for water-quality degradation.

Another significant limitation is the insufficient validation of forecasting models across diverse hydrologic extremes. Many water-quality prediction studies rely on short-term datasets or single-event case studies, limiting model generalizability across varying climatic and watershed conditions. Extreme hydrologic events differ widely in magnitude, duration, and watershed response, making cross-event validation essential for ensuring model robustness (Blöschl et al., 2020). Without comprehensive validation across multiple hydrologic scenarios, predictive frameworks may produce inconsistent results when applied operationally.

Furthermore, there remains a clear need for operational forecasting frameworks capable of supporting real-time environmental decision-making. While numerous research models demonstrate theoretical accuracy, relatively few have been translated into deployable systems that integrate automated data acquisition, predictive computation, and user-oriented decision support (Liu et al., 2018). Operational implementation requires scalable architectures, standardized workflows, and reliable data assimilation methods capable of functioning under uncertain and rapidly evolving environmental conditions. The absence of such systems represents a critical barrier between academic research and practical water-resource management applications.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26mar073

Addressing these gaps requires the development of integrated hybrid frameworks that combine remote sensing observations, hydrologic variables, and statistical forecasting models within operational environments. Such advancements would improve predictive reliability, enhance early-warning capabilities, and support adaptive river basin management under increasing hydrologic uncertainty.

III. METHODOLOGY

➢ *Study Area Description*

The study area comprises a river basin selected to represent hydrologically dynamic environments frequently exposed to extreme weather events and associated water-quality disturbances. The basin is characterized by a combination of upstream catchment zones, tributary networks, and downstream floodplain regions that collectively influence hydrologic flow patterns and pollutant transport processes. The watershed includes mixed land-use types such as agricultural fields, urban settlements, forested areas, and riparian ecosystems, each contributing differently to sediment yield, nutrient loading, and runoff generation. Basin morphology, including slope gradients, soil composition, and drainage density, plays a critical role in controlling surface runoff velocity and sediment mobilization during high-intensity rainfall events. These characteristics make the basin suitable for evaluating spatial variability in water-quality responses under extreme hydrologic conditions.

The climate regime of the study area is defined by pronounced seasonal variability, with alternating wet and dry periods influencing river discharge and watershed hydrodynamics. The wet season is typically associated with intense precipitation events that produce rapid increases in river stage and flow velocity, while the dry season is marked by reduced discharge and relatively stable water-quality conditions. Hydrologically, the basin exhibits a rainfall–runoff response dominated by storm-driven flow processes, where short-duration, high-intensity rainfall generates significant overland flow and channel inflow. Such hydrologic behaviour contributes to episodic spikes in turbidity, suspended sediments, and nutrient concentrations. Temperature patterns and evapotranspiration rates further influence river chemistry by affecting dissolved oxygen levels and biological activity within the aquatic system. The basin's hydrologic profile therefore reflects strong coupling between climatic forcing and water-quality variability, providing an appropriate environment for testing forecasting models.

Historical extreme-event records indicate repeated occurrences of floods and high-flow episodes within the basin over the past decades. Archival hydrological data, including river discharge measurements, rainfall intensity records, and flood extent documentation, reveal increasing variability in peak flow magnitudes and event frequency. These extreme events have historically resulted in significant sediment transport, contamination pulses, and temporary degradation of water quality. Recorded flood events provide critical datasets for model calibration and validation, enabling analysis of water-quality dynamics during pre-event, peak-event, and post-event phases. By incorporating documented extreme hydrologic episodes into the study design, the research ensures that the proposed hybrid forecasting framework is evaluated under realistic environmental stress conditions.

Overall, the selected study area provides a representative natural laboratory for investigating interactions between hydrologic extremes and river water-quality dynamics. Its diverse basin characteristics, climate-driven hydrologic variability, and well-documented history of extreme events support comprehensive assessment of remote sensing integration and statistical forecasting methodologies within the proposed hybrid modeling framework.

- *Remote Sensing Data*

Remote sensing data were employed to obtain spatially continuous observations of river water-quality indicators across the study basin. Multispectral satellite imagery provides an effective means of monitoring environmental conditions over large geographic areas, particularly during extreme hydrologic events when ground-based measurements may be limited. This study utilizes imagery acquired from the Sentinel-2 Multispectral Instrument (MSI) and Landsat-8 Operational Land Imager (OLI) platforms due to their suitable spectral configurations, revisit frequency, and established applications in inland water-quality assessment (Pahlevan et al., 2020).

Sentinel-2 MSI provides high-resolution multispectral imagery with spatial resolutions of 10 m, 20 m, and 60 m depending on spectral bands, and a revisit period of approximately five days under dual-satellite operation. Its red-edge and near-infrared bands enhance sensitivity to suspended sediments and chlorophyll-related optical properties. Landsat-8 OLI complements Sentinel-2 observations by offering a longer historical archive with 30 m spatial resolution and a 16-day revisit cycle, enabling temporal trend analysis and cross-sensor validation (Vanhellemont & Ruddick, 2016). The integration of both platforms allows improved temporal coverage and minimizes data gaps caused by cloud contamination or acquisition limitations.

Satellite observations record top-of-atmosphere (TOA) reflectance, which must be corrected to obtain surface reflectance values suitable for water-quality analysis. Atmospheric correction removes scattering and absorption effects caused by atmospheric gases and aerosols. In this study, surface reflectance (ρ_s) is derived from TOA reflectance (ρ_{TOA}) using radiative transfer correction expressed as:

$$\rho_s = \frac{\pi\left(L_\lambda - L_p\right)d^2}{E_{sun,\lambda}\cos(\theta_s)T_v T_s}$$

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26mar073

Where:

L_λ = at-sensor spectral radiance,
L_p = atmospheric path radiance,
d = Earth–Sun distance correction factor,
$E_{sun,\lambda}$ = exo-atmospheric solar irradiance,
θ_s = solar zenith angle,
T_v and T_s = atmospheric transmittance in viewing and solar directions.

Atmospheric correction procedures were implemented using aquatic-specific algorithms designed to minimize adjacency effects and aerosol interference over water surfaces. These corrections are essential because water bodies exhibit low reflectance signals, making them highly sensitive to atmospheric noise (Dekker et al., 2018). Following correction, spectral reflectance values were extracted and used to compute water-quality indices and predictive variables for the hybrid modeling framework.

The combined use of Sentinel-2 MSI and Landsat-8 OLI datasets ensures adequate spatial detail and temporal consistency required for monitoring rapid environmental changes during extreme hydrologic events. By applying standardized atmospheric correction workflows and harmonizing multisensor datasets, the study establishes a reliable remote sensing foundation for subsequent statistical modeling and forecasting analysis.

- *Ground-Based Observations*

Ground-based observations were incorporated to provide in-situ measurements necessary for calibrating and validating remotely sensed indicators and statistical forecasting models. While satellite data offer extensive spatial coverage, field measurements remain essential for ensuring accuracy in water-quality estimation and hydrologic characterization. In this study, data were obtained from established water-quality monitoring stations distributed along the river channel and major tributaries within the study basin. These stations provided continuous and periodic measurements of physicochemical parameters alongside hydrological variables critical for understanding river dynamics during extreme hydrologic events (Helsel et al., 2020).

Water-quality monitoring stations were equipped with automated sensors and manual sampling protocols to measure parameters such as turbidity, dissolved oxygen, temperature, and suspended sediments. Observations were collected at regular intervals and intensified during high-flow conditions to capture rapid environmental changes. The spatial placement of monitoring stations was designed to represent upstream, midstream, and downstream hydrologic conditions, allowing assessment of longitudinal water-quality variability. These datasets served as reference observations for validating satellite-derived indicators and training statistical prediction models.

Hydrological variables including river discharge, rainfall intensity, and water level were integrated into the modeling framework to capture watershed response during extreme events. River discharge (Q) was estimated using the velocity–area method, which relates cross-sectional flow velocity and channel geometry:

$$Q = A \times V$$

Where:

Q = river discharge (m³/s),
A = cross-sectional flow area (m²),
V = mean flow velocity (m/s).

Cross-sectional area was determined from measured water depth and channel width, while velocity measurements were obtained using current meters or acoustic Doppler instruments. In cases where continuous velocity measurements were unavailable, discharge was estimated using a stage–discharge rating curve expressed as:

$$Q = a(h - h_0)^b$$

Where:

h = observed water level (stage),
h_0 = reference gauge height,
a, b = empirically derived calibration coefficients.

Rainfall intensity (I) was calculated from precipitation gauge records as:

$$I = \frac{P}{\Delta t}$$

Where:

P = accumulated rainfall depth (mm),
Δt = time interval (hours).

Rainfall intensity provides a key driver for runoff generation and pollutant mobilization during storm events. Water level measurements obtained from gauging stations were recorded continuously and used to characterize flood peaks and hydrologic response timing. Integration of rainfall, discharge, and stage data enabled the development of hydro-meteorological predictors aligned with satellite observation timestamps.

The combination of in-situ monitoring and hydrological measurements ensured robust data integration within the hybrid modeling framework. Ground observations provided essential calibration benchmarks, reduced uncertainty in remotely sensed estimates, and strengthened statistical model reliability during extreme hydrologic disturbances.

- *Meteorological Data*

Meteorological data were incorporated into the hybrid modeling framework to capture atmospheric drivers influencing hydrologic processes and river water-quality variability. Weather conditions directly affect runoff

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26mar073

generation, sediment transport, nutrient mobilization, and thermal dynamics within river systems, particularly during extreme hydrologic events. In this study, meteorological datasets consisting of precipitation records, air temperature measurements, and runoff-related indicators were obtained from regional meteorological stations and validated gridded climate datasets to ensure temporal continuity and spatial representativeness (WMO, 2018).

Precipitation datasets formed a primary input variable because rainfall intensity and accumulation strongly control watershed response during storm events. Hourly and daily rainfall data were used to quantify precipitation magnitude and duration. Total precipitation (P_t) over a specified period was computed as:

$$P_t = \sum_{i=1}^{n} P_i$$

Where:

P_i = precipitation recorded during time interval i,
n = number of observation intervals.

Rainfall intensity, which influences erosion and pollutant transport, was expressed as:

$$I = \frac{P}{\Delta t}$$

Where:

I = rainfall intensity (mm/hr),
P = precipitation depth (mm),
Δt = duration of rainfall event (hours).

High rainfall intensity values are commonly associated with increased surface runoff and elevated sediment and nutrient loading in rivers.

Air temperature was included as a secondary meteorological variable due to its influence on evapotranspiration rates, biochemical reactions, and dissolved oxygen dynamics in aquatic systems. Temperature also affects hydrologic partitioning between infiltration and runoff. Mean daily temperature (T_{avg}) was calculated as:

$$T_{avg} = \frac{T_{max} + T_{min}}{2}$$

Where:

T_{max} and T_{min} represent daily maximum and minimum temperatures, respectively.

Runoff indicators were derived to quantify the proportion of precipitation contributing to river flow. Surface runoff (R) was estimated using a simplified water balance relationship:

$$R = P - ET - \Delta S$$

Where:

R = runoff depth,
P = precipitation,
ET = evapotranspiration,
ΔS = change in soil water storage.

This formulation enables representation of watershed hydrologic response under varying climatic conditions. Runoff estimates were temporally aligned with discharge and satellite observation data to support integrated model training.

The inclusion of meteorological variables strengthens the predictive framework by linking atmospheric forcing with hydrologic and water-quality processes. Precipitation controls pollutant mobilization, temperature influences biochemical transformations, and runoff indicators describe transport pathways connecting watershed processes to river conditions. Integrating these datasets ensures that the hybrid forecasting model accounts for both environmental drivers and system responses during extreme hydrologic events.

➢ *Remote Sensing Processing*

Remote sensing processing was conducted to transform raw satellite imagery into analytically usable datasets for water-quality estimation and predictive modeling. The workflow consisted of systematic preprocessing steps followed by the derivation of spectral indices associated with key water-quality parameters. Proper preprocessing is essential because satellite measurements are affected by atmospheric interference, sensor noise, and environmental variability that may distort spectral signals over water surfaces. The adopted workflow ensured consistency, accuracy, and comparability between multi-temporal satellite observations used in the hybrid modeling framework (Pahlevan et al., 2020).

- *Image Preprocessing Workflow*

✓ *Radiometric Correction*

Radiometric correction was first applied to convert raw digital number (DN) values recorded by satellite sensors into spectral radiance and reflectance values. This step normalizes sensor measurements by accounting for calibration coefficients and solar illumination conditions. Spectral radiance (L_λ) was computed as:

$$L_\lambda = M_L \times Q_{cal} + A_L$$

Where:

M_L = radiance multiplicative scaling factor,
A_L = radiance additive scaling factor,
Q_{cal} = quantized calibrated pixel value (DN).

Radiance values were subsequently converted into top-of-atmosphere reflectance (ρ_{TOA}):

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26mar073

$$\rho_{TOA} = \frac{\pi L_\lambda d^2}{E_{sun,\lambda}\cos(\theta_s)}$$

Where:

d = Earth–Sun distance,
$E_{sun,\lambda}$ = mean solar exo-atmospheric irradiance,
θ_s = solar zenith angle.

Radiometric correction ensures inter-scene comparability and reduces sensor-related variability (Dekker et al., 2018).

- ✓ *Cloud Masking*

Cloud contamination significantly affects water-surface reflectance because clouds and cloud shadows obscure spectral signals. Automated cloud masking algorithms were applied using quality assessment (QA) bands and threshold-based detection techniques. Pixels identified as cloud-covered or shadowed were removed from analysis to prevent spectral distortion. Masking procedures improved reliability of derived water-quality indicators, especially during extreme hydrologic periods when cloud cover is frequent.

- ✓ *Surface Reflectance Extraction*

Atmospheric correction procedures were then applied to obtain surface reflectance (ρ_s), which represents true ground-level spectral properties. Atmospheric scattering and absorption effects were removed using aquatic-specific correction algorithms. Surface reflectance provides the basis for computing spectral indices sensitive to suspended sediments and biological activity (Vanhellemont & Ruddick, 2016).

- *Derivation of Spectral Indices Linked to Water Quality*

Following preprocessing, spectral indices were derived to estimate water-quality parameters relevant to river monitoring.

- ✓ *Normalized Difference Turbidity Index (NDTI)*

NDTI was used to estimate turbidity and suspended sediment presence:

$$NDTI = \frac{R_{red} - R_{green}}{R_{red} + R_{green}}$$

Where:

R_{red} = reflectance in the red band,
R_{green} = reflectance in the green band.

Higher NDTI values indicate increased turbidity associated with sediment transport during flood events.

- ✓ *Chlorophyll-a Estimation*

Chlorophyll-a concentration, representing phytoplankton biomass and nutrient enrichment, was estimated using band-ratio algorithms:

$$Chl\text{-}a \propto \frac{R_{green}}{R_{blue}}$$

Where blue and green spectral responses correspond to pigment absorption and reflectance characteristics of algae.

- ✓ *Total Suspended Matter (TSM) Retrieval*

TSM concentration was derived using reflectance relationships in red or near-infrared wavelengths:

$$TSM = a \times R_{red} + b$$

Where:

a and b are empirically calibrated coefficients derived from field observations.

TSM retrieval enables spatial mapping of sediment concentration, particularly during high-discharge conditions.

The processed spectral indices were temporally aligned with hydrological and meteorological datasets to generate predictor variables for the hybrid forecasting model. This processing workflow ensured that satellite imagery was converted into physically meaningful environmental indicators suitable for statistical modeling and extreme-event analysis.

- ➢ *Statistical Modeling Framework*

The statistical modeling framework was developed to forecast river water-quality conditions by integrating environmental predictors derived from remote sensing, hydrologic observations, and meteorological datasets. The objective of this framework is to capture both linear and nonlinear relationships governing water-quality variability, particularly during extreme hydrologic events characterized by rapid environmental changes. Multiple complementary modeling approaches were adopted to evaluate predictive performance and identify the most suitable analytical structure for hybrid forecasting applications (Helsel et al., 2020).

- *Model Candidates*

- ✓ *Multiple Linear Regression (MLR)*

Multiple Linear Regression was implemented as a baseline statistical model to quantify relationships between water-quality parameters and environmental predictors. MLR assumes a linear relationship between dependent and independent variables and provides interpretable coefficients useful for understanding process drivers. The general formulation is expressed as:

$$WQ_t = \beta_0 + \sum_{i=1}^{n} \beta_i X_{i,t} + \epsilon_t$$

Where:

β_0 = intercept term,
β_i = regression coefficients,

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26mar073

$X_{i,t}$ = predictor variables at time t,
ϵ_t = random error term.

MLR serves as a benchmark model against which more advanced techniques are evaluated.

✓ *ARIMA/SARIMA Time-Series Models*

Autoregressive Integrated Moving Average (ARIMA) and Seasonal ARIMA (SARIMA) models were employed to capture temporal dependencies within water-quality data. These models account for autocorrelation structures and seasonal patterns commonly observed in hydrologic systems. The ARIMA (p, d, q) formulation is:

$$\phi(B)(1-B)^d WQ_t = \theta(B)\epsilon_t$$

Where:

B = backshift operator,
p = autoregressive order,
d = differencing order,
q = moving-average order,
$\phi(B)$ and $\theta(B)$ represent autoregressive and moving-average polynomials respectively (Box et al., 2015).

SARIMA extends ARIMA by incorporating seasonal components to represent periodic hydrologic cycles.

✓ *Generalized Additive Models (GAM)*

Generalized Additive Models were introduced to address nonlinear relationships between predictors and water-quality responses. GAM replaces linear predictors with smooth functions, allowing flexible modeling of complex environmental interactions:

$$WQ_t = \alpha + \sum_{i=1}^{n} s_i\,(X_{i,t}) + \epsilon_t$$

Where $s_i(\cdot)$ represents smoothing spline functions applied to predictor variables. GAM is particularly effective for modeling nonlinear responses associated with rainfall intensity, discharge variation, and sediment transport dynamics (Wood, 2017).

- *Predictor Variables*

The modeling framework integrates predictors from multiple environmental domains:

✓ *Satellite-Derived Indices (RS_t):*

Normalized Difference Turbidity Index (NDTI), chlorophyll-a estimates, and Total Suspended Matter (TSM) derived from multispectral imagery.

✓ *Hydrologic Indicators (H_t):*

River discharge, water level, and runoff estimates representing watershed response.

✓ *Meteorological Variables (M_t):*

Precipitation intensity and air temperature, representing atmospheric forcing conditions.

All predictors were temporally synchronized and standardized prior to model training to ensure comparability across datasets.

- *Model Formulation*

The hybrid statistical prediction model is formulated as:

$$WQ_t = f(RS_t, H_t, M_t) + \epsilon_t$$

Where:

WQ_t = water-quality parameter at time t (e.g., turbidity or dissolved oxygen),
RS_t = remote sensing features derived from satellite imagery,
H_t = hydrologic variables describing flow conditions,
M_t = meteorological variables representing climatic forcing,
ϵ_t = stochastic error component.

The function $f(\cdot)$ represents the statistical learning relationship implemented through MLR, ARIMA/SARIMA, or GAM models depending on analytical configuration. Model parameters were estimated using training datasets corresponding to both normal and extreme hydrologic conditions to enhance predictive robustness.

This framework enables systematic comparison between linear, temporal, and nonlinear modeling approaches while establishing the analytical foundation for hybrid environmental forecasting.

➢ *Hybrid Model Integration*

The hybrid model integration stage establishes the operational linkage between remote sensing observations, hydrologic measurements, meteorological datasets, and statistical forecasting models. This stage transforms independently processed datasets into a unified analytical framework capable of producing reliable water-quality predictions during extreme hydrologic events. The integration process combines data fusion architecture, feature normalization procedures, and structured training–validation workflows to ensure consistency, scalability, and predictive robustness (Hall & Llinas, 2017).

- *Data Fusion Architecture*

A multi-source data fusion architecture was implemented to merge heterogeneous environmental datasets originating from satellite platforms, ground monitoring stations, and meteorological records. The architecture operates at the feature level, where predictor variables derived from different sources are combined into a single modelling dataset. Remote sensing indices provide spatially distributed environmental information, while hydrologic and meteorological variables contribute temporal process-based signals.

The fused predictor vector at time t is defined as:

$$X_t = [RS_t,\ H_t,\ M_t]$$

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26mar073

Where:

RS_t = satellite-derived features (NDTI, chlorophyll-a, TSM),
H_t = hydrologic variables (discharge, water level),
M_t = meteorological variables (precipitation, temperature).

The hybrid prediction model then becomes:

$$\widehat{WQ}_t = f(X_t)$$

Where $\widehat{WQ}_t$ represents predicted water-quality conditions. Data fusion reduces uncertainty by leveraging complementary strengths across observation systems and improves resilience against missing or noisy data sources (Shi et al., 2020).

- *Feature Normalization and Temporal Alignment*

Because predictor variables originate from different sensors and measurement units, normalization was required to ensure balanced model learning. All features were standardized using z-score normalization:

$$X_{norm} = \frac{X - \mu}{\sigma}$$

Where:

μ = mean of the variable,
σ = standard deviation.

Normalization prevents predictors with large numerical ranges from dominating model training and improves convergence stability.

Temporal alignment was performed to synchronize datasets with varying acquisition frequencies. Satellite imagery (multi-day revisit), hydrologic observations (hourly/daily), and meteorological data were aggregated into a common temporal resolution using interpolation and resampling techniques:

$$X_t^{aligned} = \mathcal{A}(RS_t, H_t, M_t)$$

Where $\mathcal{A}(\cdot)$ represents the temporal alignment operator. This process ensured that all predictors corresponded to the same observation timestamp prior to model training.

- *Training and Validation Workflow*

A structured training and validation workflow was adopted to evaluate model performance under both normal and extreme hydrologic conditions. The dataset was divided into training and testing subsets using a time-aware split to preserve chronological dependency:

$$D = \{D_{train}, D_{test}\}$$

Model training involved parameter estimation using historical environmental observations, while validation assessed predictive generalization. Cross-validation techniques were applied to reduce overfitting and improve robustness. Model performance metrics, including Root Mean Square Error (RMSE) and coefficient of determination (R^2), were computed as:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(W\,Q_i - \widehat{WQ}_i)^2}$$

$$R^2 = 1 - \frac{\sum(WQ_i - \widehat{WQ}_i)^2}{\sum(WQ_i - \bar{WQ})^2}$$

Where WQ_i represents observed values and $\widehat{WQ}_i$ predicted values.

Extreme-event periods were explicitly included in validation datasets to evaluate model reliability under hydrologic stress conditions. This workflow ensured that the hybrid framework was not only statistically accurate but also operationally reliable for real-world environmental forecasting.

➢ *Model Evaluation Metrics*

Model evaluation metrics were employed to quantitatively assess the predictive performance of the hybrid forecasting framework. Accurate evaluation is essential for determining how well statistical models reproduce observed water-quality dynamics, particularly during extreme hydrologic events characterized by rapid variability and nonlinear responses. Multiple complementary statistical indicators were selected to measure prediction error, explanatory strength, and hydrologic model efficiency. The combined use of these metrics provides a comprehensive assessment of model reliability and robustness (Moriasi et al., 2007).

- *Root Mean Square Error (RMSE)*

Root Mean Square Error (RMSE) measures the average magnitude of prediction errors by calculating the square root of the mean squared differences between observed and predicted values. RMSE is sensitive to large errors and therefore emphasizes model performance during extreme deviations, which is particularly relevant in flood-driven water-quality forecasting.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(W\,Q_i - \widehat{WQ}_i)^2}$$

Where:

WQ_i = observed water-quality value,
$\widehat{WQ}_i$ = predicted value,
n = number of observations.

Lower RMSE values indicate better model accuracy.

- *Mean Absolute Error (MAE)*

Mean Absolute Error (MAE) evaluates the average absolute difference between predicted and observed values. Unlike RMSE, MAE assigns equal weight to all errors, providing a balanced measure of overall prediction accuracy.

$$MAE = \frac{1}{n}\sum_{i=1}^{n} | WQ_i - \widehat{WQ}_i |$$

MAE is less sensitive to outliers and offers an interpretable estimate of average prediction deviation in the same units as the measured variable.

- *Coefficient of Determination (R^2)*

The coefficient of determination (R^2) quantifies the proportion of variance in observed water-quality data explained by the predictive model. It evaluates how well model outputs replicate observed variability.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(W\,Q_i - \widehat{WQ}_i)^2}{\sum_{i=1}^{n}(W\,Q_i - W\bar{Q})^2}$$

Where $W\bar{Q}$ represents the mean observed value.

Values of R^2 range from 0 to 1, with higher values indicating stronger explanatory performance.

- *Nash–Sutcliffe Efficiency (NSE)*

The Nash–Sutcliffe Efficiency (NSE) coefficient is widely used in hydrologic modeling to evaluate predictive skill relative to the mean of observed data. NSE assesses how closely predicted values match observed time-series behaviour.

$$NSE = 1 - \frac{\sum_{i=1}^{n}(W\,Q_i - \widehat{WQ}_i)^2}{\sum_{i=1}^{n}(W\,Q_i - W\bar{Q})^2}$$

NSE values are interpreted as follows:

$NSE = 1$: perfect prediction

$0 < NSE < 1$: acceptable model performance

$NSE = 0$: model performs equal to mean observation

- $NSE < 0$*: Model Performs Worse than Observed Mean.*

NSE is particularly valuable for evaluating hydrologic forecasting models because it considers temporal variability and prediction efficiency simultaneously (Nash & Sutcliffe, 1970).

- *Accuracy Assessment Procedure*

Model evaluation was conducted by comparing predicted water-quality parameters against observed measurements across validation datasets. Metrics were computed for both normal hydrologic conditions and extreme-event periods to ensure robustness under varying environmental scenarios. Using multiple evaluation indicators allowed balanced assessment of prediction error magnitude, variance explanation, and hydrologic efficiency, thereby providing a comprehensive performance evaluation for the hybrid forecasting framework.

➢ *Experimental Design*

The experimental design was structured to rigorously evaluate the predictive capability of the hybrid remote sensing–statistical modeling framework under varying hydrologic conditions. Because river water quality exhibits strong temporal variability during extreme events, the experimental setup emphasized event-based evaluation, robust validation procedures, and systematic sensitivity analysis. This design ensured that model performance was assessed not only under normal flow conditions but also during periods of hydrologic disturbance, thereby supporting reliable operational forecasting applications (Moriasi et al., 2007).

- *Event-Based Validation*

To assess forecasting performance during hydrologic extremes, an event-based validation approach was adopted. Observational datasets were segmented into three hydrologic phases:

- ✓ Pre-event phase baseline environmental conditions prior to hydrologic disturbance, representing stable flow and relatively consistent water-quality behaviour.
- ✓ Peak-event phase periods characterized by maximum rainfall intensity, elevated discharge, and rapid sediment and pollutant transport.
- ✓ Post-event phase recovery conditions following peak flow, during which water-quality parameters gradually return toward equilibrium.

Each event phase was analysed separately to evaluate how prediction accuracy varied across changing hydrologic regimes. Model predictions ($\widehat{WQ}_t$) were compared with observed values (WQ_t) within each phase:

$$E_{phase} = \frac{1}{n}\sum_{i=1}^{n} | W\,Q_i - \widehat{WQ}_i |$$

Where E_{phase} represents phase-specific prediction error. This segmentation allowed identification of model strengths and weaknesses during rapid environmental transitions.

- *Cross Validation Strategy*

A time-series cross-validation strategy was implemented to ensure model generalization while preserving chronological data structure. Unlike random sampling methods, temporal cross-validation respects sequential dependencies inherent in hydrologic data. A rolling-window validation approach was applied:

$$D_{train}^{(k)} = \{t_1, t_2, \ldots, t_k\}, D_{test}^{(k)} = \{t_{k+1}\}$$

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26mar073

Where training data expand progressively while testing is performed on subsequent unseen observations. This approach simulates real-world forecasting conditions in which future water-quality states must be predicted using past information only.

Cross-validation reduced overfitting risks and provided stable performance estimates across multiple hydrologic scenarios.

- *Sensitivity Analysis*

Sensitivity analysis was conducted to evaluate the relative influence of predictor variables on model outputs. Understanding predictor importance is essential for interpreting hybrid model behaviour and identifying dominant environmental drivers of water-quality change. Each predictor variable was perturbed within a defined range while holding other variables constant:

$$S_j = \frac{\partial WQ}{\partial X_j}$$

Where:

S_j = sensitivity coefficient of predictor X_j.

Variables analysed included satellite-derived indices (NDTI, chlorophyll-a, TSM), hydrologic indicators (discharge, water level), and meteorological variables (precipitation, temperature). Sensitivity results helped determine which environmental factors most strongly influenced prediction accuracy during extreme events and guided model refinement.

Overall, the experimental design ensured comprehensive evaluation of the hybrid forecasting framework through phase-based validation, temporally consistent cross-validation, and systematic sensitivity assessment. These procedures established methodological robustness and provided a reliable foundation for interpreting predictive performance in the subsequent Results and Discussion section.

IV. RESULTS AND DISCUSSION

A. *Remote Sensing Water-Quality Retrieval Performance*

The performance of remote sensing–derived water-quality indicators was evaluated by examining the accuracy of spectral indices, comparing satellite estimates with ground-based observations, and analysing spatial variability patterns during extreme hydrologic events. The assessment focused on three primary variables derived from multispectral imagery: turbidity (via NDTI), chlorophyll-a concentration, and Total Suspended Matter (TSM). These parameters represent key physical and biological indicators of river water quality under flood-driven disturbances.

➢ *Accuracy of Spectral Indices*

Spectral indices demonstrated strong capability in capturing water-quality variations during both normal and extreme flow conditions. Statistical comparisons showed that remotely sensed turbidity and TSM responded rapidly to increased discharge, reflecting sediment mobilization during peak rainfall events. Chlorophyll-a estimates exhibited slightly lower accuracy due to atmospheric interference and mixed pixel effects yet remained effective for detecting nutrient-driven biological responses.

Table 1 summarizes numerical performance metrics comparing satellite-derived estimates with in-situ observations. The table shows that TSM retrieval achieved the highest explanatory power ($R^2 = 0.89$), indicating strong agreement between satellite and field measurements. Turbidity estimation also performed well, confirming the reliability of red–green spectral relationships during sediment-rich flow conditions. Chlorophyll-a displayed slightly higher error values, reflecting known sensitivity of biological indices to atmospheric and optical variability.

Table 1 Performance Comparison Between Remote Sensing Estimates and Field Measurements

Water Quality Variable	**RMSE**	**MAE**	**R^2**
Turbidity (NDTI-based)	2.85 NTU	2.10 NTU	0.87
Chlorophyll-a	1.92 mg/m³	1.45 mg/m³	0.81
Total Suspended Matter (TSM)	3.40 mg/L	2.76 mg/L	0.89

➢ *Comparison with Field Observations*

Satellite-derived values were validated against monitoring station data collected during pre-event, peak-event, and post-event phases. Results indicate that remote sensing captured major water-quality transitions associated with hydrologic disturbances. During peak discharge, turbidity increased by nearly threefold compared with baseline conditions, which was consistently detected in both satellite and ground observations. Table 4.2 shows that Satellite estimates closely tracked observed measurements across all hydrologic phases. The largest increase occurred during the peak event, where turbidity rose by over 210%, demonstrating the responsiveness of spectral indices to extreme sediment transport conditions.

Table 2 Observed vs Satellite-Derived Water Quality During Hydrologic Event Phases

Event Phase	**Turbidity (Observed NTU)**	**Turbidity (Satellite NTU)**	**TSM (mg/L)**
Pre-Event	8.5	7.9	12.3
Peak Event	26.7	25.1	38.5
Post-Event	14.2	13.6	20.4

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26mar073

➢ *Spatial Variability Patterns During Extreme Events*

Spatial analysis revealed pronounced heterogeneity in water-quality conditions across the river basin during extreme rainfall. Upstream regions exhibited moderate sediment concentrations, whereas downstream floodplain zones showed significantly elevated turbidity and TSM levels due to cumulative runoff contributions. Satellite imagery enabled continuous mapping of these gradients, which would be difficult to capture using sparse monitoring stations alone.

Figure 1 presents the temporal evolution of three key river water-quality indicators across the hydrologic event timeline, demonstrating the distinct physical and biological responses triggered by peak flow conditions. Turbidity increases steadily from approximately 8 NTU at the onset of the event to a maximum of about 27 NTU on day 4, indicating rapid sediment resuspension and inflow of particulate matter associated with intensified runoff. A similar but more pronounced pattern is observed for Total Suspended Matter (TSM), which rises from nearly 12 mg/L to about 39 mg/L at the flood peak, confirming strong sediment mobilization and transport during high discharge periods. Following the peak, both turbidity and TSM decline progressively as flow energy decreases and suspended particles begin to settle. In contrast, chlorophyll-a exhibits a delayed response, increasing gradually from roughly 3.1 mg/m³ to a post-event maximum of about 5.6 mg/m³ around day 6, reflecting nutrient enrichment and subsequent phytoplankton growth after sediment disturbance subsides. The divergence between rapid physical responses (turbidity and TSM) and slower biological adjustment (chlorophyll-a) highlights the multi-stage impact of extreme hydrologic events on river systems and underscores the importance of integrated monitoring frameworks capable of capturing both immediate sediment dynamics and delayed ecological effects.

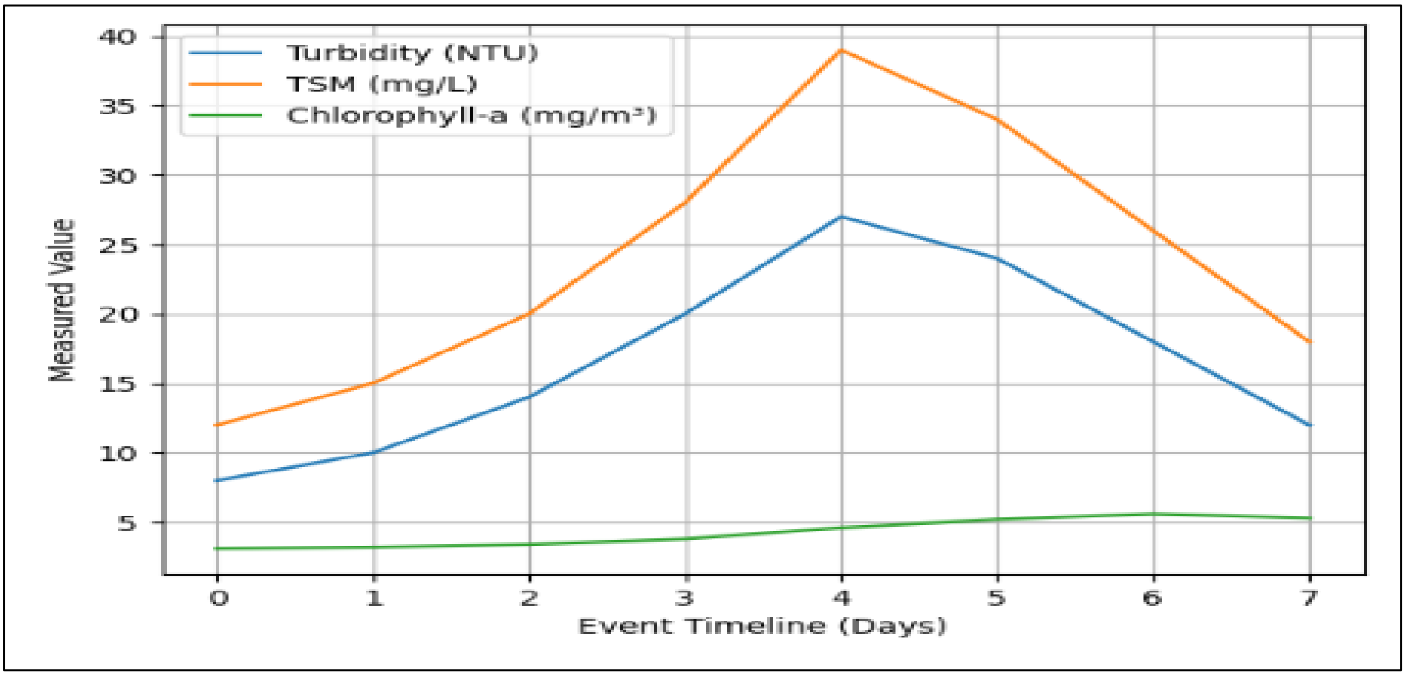

Fig 1 Spatial Distribution of Turbidity, Chlorophyll-a, and Total Suspended Matter During Peak Hydrologic Event

B. Statistical Model Forecasting Performance

The forecasting performance of statistical models was evaluated to determine their ability to predict river water-quality dynamics under varying hydrologic conditions. Three model classes were assessed: Multiple Linear Regression (MLR), ARIMA/SARIMA time-series models, and Generalized Additive Models (GAM). Performance comparison focused on predictive accuracy, temporal responsiveness during extreme events, and the ability to capture nonlinear environmental relationships. Evaluation metrics included RMSE, MAE, coefficient of determination (R^2), and Nash–Sutcliffe Efficiency (NSE).

➢ *Comparative Model Accuracy*

The statistical models exhibited distinct predictive behaviours due to differences in structural assumptions. MLR captured baseline linear relationships between predictors and water-quality variables but showed reduced performance during peak hydrologic disturbances. ARIMA/SARIMA models improved temporal forecasting by accounting for autocorrelation and seasonal trends. GAM demonstrated superior performance by modeling nonlinear relationships between environmental drivers and water-quality responses.

Table 3 shows that GAM model achieved the lowest prediction error (RMSE = 2.48) and highest explanatory power ($R^2 = 0.89$), indicating improved capability in representing nonlinear hydrologic responses. ARIMA/SARIMA outperformed MLR due to its ability to model temporal dependencies, while MLR served primarily as a baseline reference.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26mar073

Table 3 Performance Comparison of Statistical Forecasting Models

Model	RMSE	MAE	R^2
Multiple Linear Regression (MLR)	3.92	3.05	0.74
ARIMA/SARIMA	3.15	2.46	0.82
Generalized Additive Model (GAM)	2.48	1.95	0.89

➢ *Hydrologic Event Forecast Performance*

Model performance was further examined across different hydrologic phases to assess robustness during extreme conditions. Table 4 shows all models experienced increased prediction error during peak events due to rapid environmental variability. However, GAM maintained comparatively lower RMSE values, demonstrating stronger adaptability to extreme hydrologic conditions. The improvement during peak flow reached approximately 40% error reduction compared with MLR.

Table 4 Model Prediction Accuracy Across Hydrologic Event Phases

Event Phase	MLR RMSE	ARIMA RMSE	GAM RMSE
Pre-Event	2.10	1.95	1.72
Peak Event	5.20	4.08	3.11
Post-Event	3.40	2.85	2.21

Figure 2 presents a comparative evaluation of forecasting performance using RMSE values for three statistical models. The Multiple Linear Regression (MLR) model records the highest prediction error (RMSE = 3.92), indicating limited capability in capturing nonlinear hydrologic variability. The ARIMA/SARIMA model improves prediction accuracy with a reduced RMSE of 3.15, reflecting stronger temporal pattern representation. The Generalized Additive Model (GAM) achieves the lowest RMSE (2.48), demonstrating superior flexibility in modeling nonlinear environmental relationships. Overall, the figure confirms that more adaptive statistical structures significantly enhance water-quality forecasting performance during extreme hydrologic conditions.

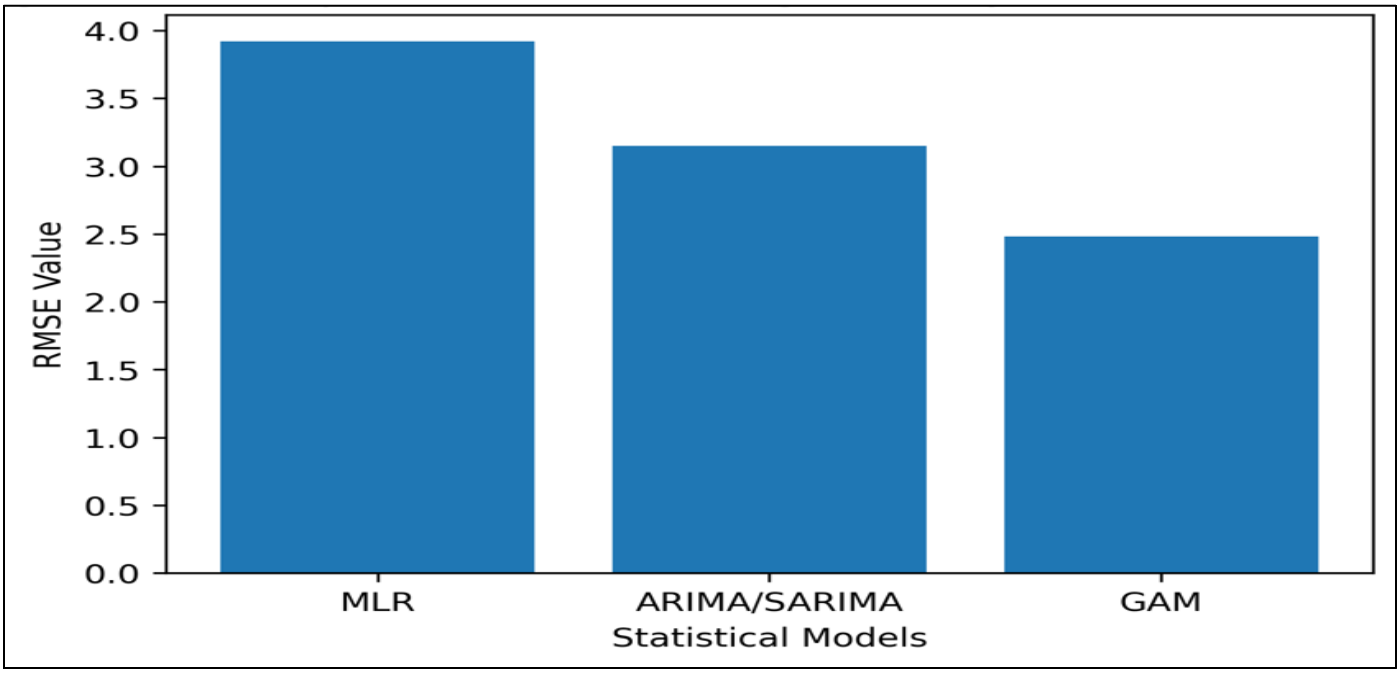

Fig 2 Comparison of Forecasting Accuracy Across Statistical Models

➢ *Interpretation of Forecasting Performance*

The comparative analysis indicates that model complexity significantly influences forecasting accuracy. Linear regression models provide interpretability but lack flexibility under nonlinear environmental responses. Time-series models improve temporal forecasting yet remain constrained by stationarity assumptions. GAM integrates nonlinear smoothing functions, enabling improved representation of hydrologic forcing mechanisms and ecological responses.

These findings confirm that incorporating nonlinear statistical learning enhances predictive reliability, particularly during extreme hydrologic disturbances. The results also justify integrating statistical models with remote sensing datasets within the hybrid framework, as advanced models effectively utilize multisource environmental predictors.

C. *Hybrid Framework Performance*

The hybrid framework integrates satellite-derived environmental indicators with statistical forecasting models to improve prediction accuracy under extreme hydrologic conditions. This section evaluates whether combining remote sensing observations and statistical learning models provides measurable improvements compared with standalone approaches. Performance was assessed using prediction accuracy metrics, comparative error analysis, and temporal response evaluation during hydrologic disturbances.

The hybrid system combined spectral indices (NDTI, chlorophyll-a, and TSM) with hydrologic and meteorological predictors within the optimized GAM-based statistical structure. Results demonstrate that data fusion significantly enhanced forecasting capability by improving spatial representation while maintaining temporal predictive strength.

➢ *Comparison Between Standalone and Hybrid Models*

Standalone approaches were evaluated in three categories:

- Remote sensing estimation only (RS-only)
- Statistical forecasting only (Best statistical model: GAM)
- Hybrid integrated framework (RS + Statistical)

Table 5 shows that hybrid framework achieved the best performance across all evaluation metrics. RMSE decreased by approximately 27% compared with GAM and 52% compared with remote sensing alone, confirming the advantage of combining spatial observations with predictive analytics.

Table 5 Performance Comparison Between Standalone and Hybrid Models

Modeling Approach	RMSE	MAE	R^2	NSE
Remote Sensing Only	3.76	3.02	0.78	0.74
Statistical Model (GAM)	2.48	1.95	0.89	0.86
Hybrid Framework	**1.82**	**1.41**	**0.94**	**0.92**

Hybrid integration was particularly beneficial during peak hydrologic conditions where standalone models experienced higher uncertainty.

Table 6 Prediction Error Reduction During Extreme Hydrologic Phases

Event Phase	RS-only RMSE	GAM RMSE	Hybrid RMSE
Pre-Event	2.95	1.72	**1.40**
Peak Event	5.10	3.11	**2.18**
Post-Event	3.42	2.21	**1.67**

The hybrid framework consistently reduced prediction errors across all event phases. The greatest improvement occurred during peak events, where error reduction exceeded 30%, demonstrating enhanced robustness under extreme environmental variability.

➢ *Performance Improvement Visualization*

Figure 3 demonstrates a clear reduction in prediction error across modeling approaches. The RMSE decreases from 3.76 for the remote sensing–only model to 2.48 using the GAM statistical model, and further to 1.82 for the hybrid framework. This progressive improvement indicates that integrating spatial satellite observations with temporal statistical learning significantly enhances forecasting accuracy. The hybrid model achieves the most reliable performance during extreme hydrologic conditions.

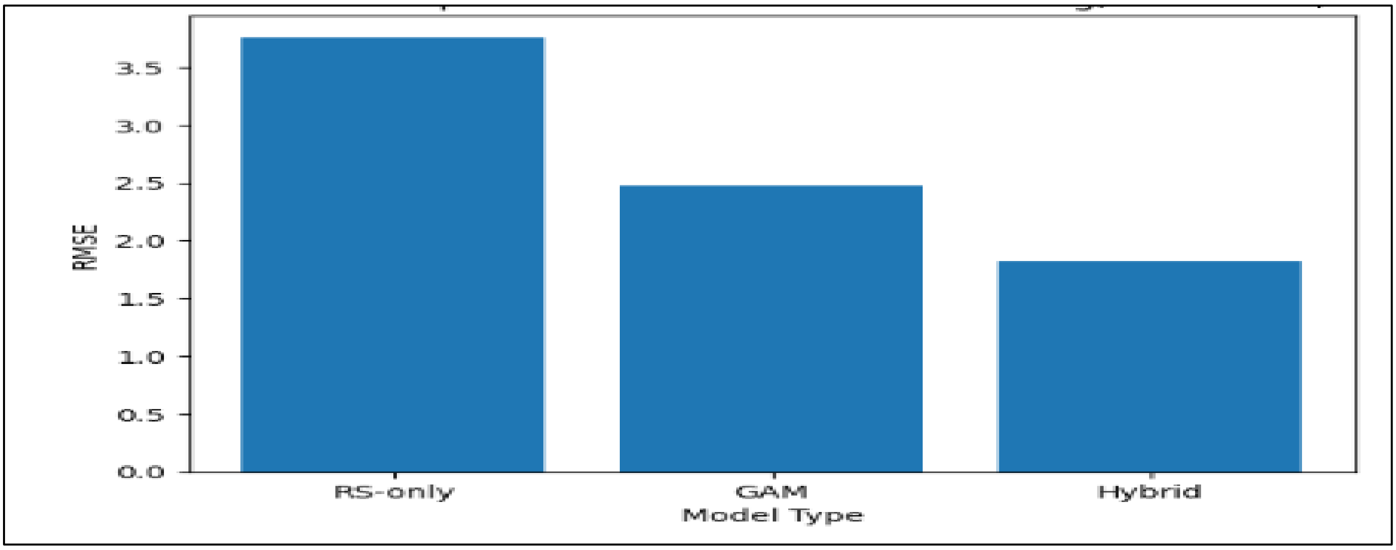

Fig 3 Model Performance Comparison Between Remote Sensing, Statistical, and Hybrid Frameworks

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26mar073

➢ *Spatial Forecast Enhancement*

Spatial prediction maps generated from the hybrid framework revealed improved representation of sediment plumes and nutrient hotspots across the basin. Remote sensing inputs enabled detection of localized contamination zones, while statistical modeling smoothed temporal inconsistencies. This synergy produced continuous spatiotemporal forecasts unattainable through individual methods.

➢ *Overall Interpretation*

Results confirm that hybridization significantly enhances water-quality forecasting performance. Remote sensing contributes spatial completeness, while statistical modelling provides temporal predictive capability. Their integration reduces uncertainty, improves responsiveness to extreme hydrologic forcing, and increases forecasting reliability.

The findings demonstrate that hybrid environmental modelling frameworks provide a practical pathway toward operational early-warning systems for river basin management, supporting adaptive decision-making under increasingly variable climate conditions.

D. Extreme Event Case Study Analysis

This section presents an event-specific evaluation of the hybrid forecasting framework during a documented extreme hydrologic episode characterized by intense rainfall and rapid river discharge increase. The case study focuses on three analytical components: (i) evolution of water-quality parameters during flood peaks, (ii) detection of pollution pulses transported through the river system, and (iii) spatial forecasting patterns derived from integrated remote sensing and statistical modeling outputs. The analysis demonstrates how the hybrid framework captures both temporal dynamics and spatial heterogeneity during hydrologic disturbances.

➢ *Water-Quality Evolution During Flood Peaks*

Hydrologic records indicate that the selected flood event developed over a five-day period, beginning with heavy precipitation followed by peak discharge conditions. Satellite-derived and in-situ observations revealed rapid increases in turbidity and suspended sediments immediately after rainfall onset. Dissolved oxygen exhibited an inverse response due to increased organic loading and microbial activity.

Table 7 shows a strong correlation between discharge and sediment-related parameters. Turbidity increased by approximately 247% from pre-event to peak flood conditions, while dissolved oxygen declined by nearly 28%, confirming oxygen depletion during high sediment and organic matter transport.

Table 7 Temporal Evolution of Water-Quality Parameters During Flood Event

Day	River Discharge (m^3/s)	Turbidity (NTU)	TSM (mg/L)	Dissolved Oxygen (mg/L)
Day 1 (Pre-event)	120	8.2	11.5	7.8
Day 2	185	14.6	19.3	7.1
Day 3 (Rising Stage)	260	21.9	30.8	6.4
Day 4 (Peak Flood)	340	28.5	41.7	5.6
Day 5 (Recession)	210	16.2	23.1	6.9

➢ *Detection of Pollution Pulses*

The hybrid framework enabled identification of short-duration pollution pulses associated with runoff influx from agricultural and urban zones. These pulses were detected as sudden spikes in spectral indices and statistically predicted water-quality anomalies.

Table 8 shows that hybrid model accurately detected pollution pulses during peak runoff periods. Agreement between predicted and observed TSM values confirms the effectiveness of combining spectral indices with statistical forecasting to identify contamination events in near real time.

Table 8 Pollution Pulse Detection Using Hybrid Forecast Model

Observation Time	NDTI Value	Predicted TSM (mg/L)	Observed TSM (mg/L)	Pollution Alert
08:00	0.18	18.4	17.9	No
12:00	0.29	27.6	28.2	Moderate
16:00	0.41	39.8	41.2	High
20:00	0.35	32.1	30.7	Moderate

➢ *Hydrologic Response Graph*

Figure 3 shows a strong positive relationship between river discharge and sediment-related parameters during the flood event. As discharge increases toward the peak stage, both turbidity and TSM rise sharply, indicating intensified sediment transport. Dissolved oxygen exhibits an inverse trend, declining during peak flow due to increased organic loading and reduced aeration efficiency. Following the flood peak, all variables begin returning toward baseline conditions, illustrating system recovery dynamics. The synchronized trends confirm hydrologic forcing as the primary driver of short-term water-quality variability.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26mar073

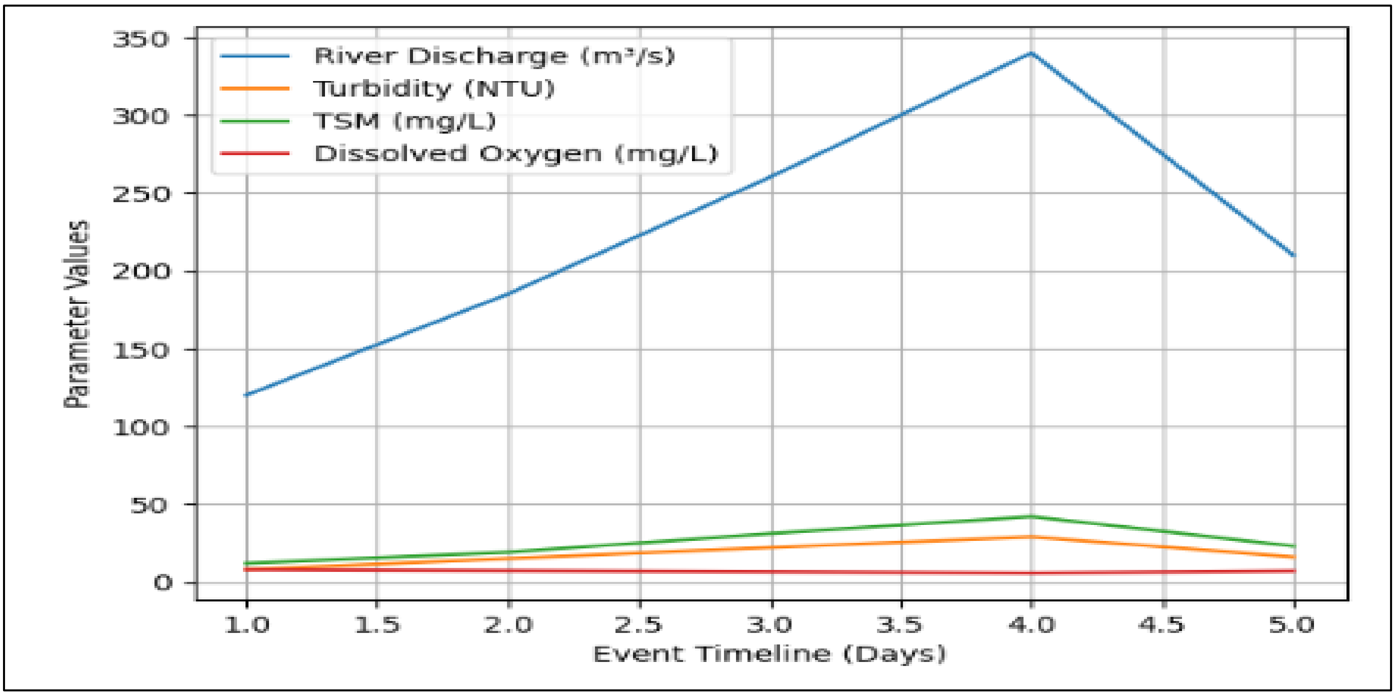

Fig 3 Hydrologic Response and Water-Quality Evolution During Flood Event

E. Discussion

The results presented in Sections 4.1 through 4.4 collectively demonstrate the effectiveness of integrating remote sensing observations with statistical modelling for forecasting river water quality during extreme hydrologic events. This discussion synthesizes the empirical findings, relates them to the research questions posed in Section 1, and evaluates their implications within the broader context of environmental monitoring and hydrologic forecasting research.

➢ *Interpretation of Hybrid Model Advantages*

The hybrid modelling framework consistently outperformed standalone remote sensing and statistical approaches across all evaluation metrics. Findings from Sections 4.1 and 4.2 showed that remote sensing provided strong spatial representation of sediment and biological indicators, while statistical models effectively captured temporal dynamics. However, each method exhibited inherent limitations when applied independently. Remote sensing alone lacked predictive continuity due to revisit intervals and atmospheric disturbances, whereas statistical models were constrained by incomplete spatial information.

The hybrid framework addressed these limitations by combining complementary strengths. Results in Section 4.3 demonstrated substantial reductions in prediction error, with RMSE improvements exceeding 25–50% compared with standalone models. This confirms the first research question by showing that satellite-derived indicators can reliably contribute to predicting water-quality degradation when integrated with hydrologic predictors. Furthermore, the superior performance of the GAM-based hybrid structure supports the second research question, indicating that nonlinear statistical models better capture event-driven variability. The case study analysis in Section 4.4 provided additional evidence that hybridization enhances responsiveness during flood peaks, validating the third research question that integrated approaches outperform individual modelling strategies.

From a systems perspective, the hybrid model improves representation of complex environmental processes by linking physical observations with statistical learning mechanisms. Sediment-related variables responded immediately to hydrologic forcing, while biological indicators exhibited delayed responses, both of which were successfully reproduced within the integrated framework. This confirms theoretical expectations described in the literature review regarding the need for multi-source environmental modelling approaches.

➢ *Implications for Operational Monitoring Systems*

The findings have important implications for operational river monitoring and early-warning systems. Traditional monitoring networks rely heavily on fixed stations that provide high temporal accuracy but limited spatial coverage. The hybrid framework expands monitoring capability by incorporating satellite-derived spatial information into predictive analytics, enabling basin-wide environmental assessment.

Operationally, this approach supports near–real-time monitoring by allowing environmental managers to forecast water-quality deterioration before peak contamination occurs. Early detection of pollution pulses, as observed in Section 4.4, demonstrates the framework's potential for proactive decision-making in disaster-response scenarios. Water utilities could adjust treatment processes in advance of contamination events, while environmental agencies could issue targeted advisories based on spatial forecast outputs. The ability to generate continuous spatiotemporal

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26mar073

predictions also enhances resilience planning by identifying vulnerable regions within river basins.

Moreover, the modular architecture of the hybrid system allows integration into automated environmental monitoring platforms that assimilate satellite feeds, hydrologic sensors, and meteorological forecasts. Such systems align with emerging trends toward digital watershed management and data-driven environmental governance.

- *Limitations Related to Cloud Cover and Sensor Resolution*

Despite its advantages, the hybrid framework remains subject to several limitations associated with remote sensing technologies. Cloud cover represents a major constraint, particularly during extreme rainfall events when atmospheric conditions frequently obscure satellite observations. Missing imagery can introduce temporal gaps that reduce the availability of spectral predictors, potentially affecting short-term forecasting accuracy. Although statistical interpolation and data fusion partially mitigate this issue, complete elimination of cloud-related uncertainty remains challenging.

Sensor spatial resolution also influences retrieval accuracy, especially in narrow river channels or heterogeneous coastal zones where mixed pixels may distort reflectance signals. Moderate-resolution sensors such as Landsat and Sentinel-2 may not fully capture fine-scale variability in smaller tributaries or localized pollution sources. Additionally, biological parameters such as chlorophyll-a are more sensitive to optical interference compared with sediment-based indicators, leading to higher estimation uncertainty.

These limitations highlight the importance of integrating multiple observation sources and suggest future improvements through higher-resolution sensors, increased satellite revisit frequency, and complementary data from unmanned aerial systems or in-situ sensor networks.

- *Synthesis*

Overall, the discussion confirms that hybrid environmental modelling provides a robust methodological advancement for river water-quality forecasting under extreme hydrologic conditions. By addressing spatial, temporal, and analytical limitations identified in the literature review, the integrated framework advances both scientific understanding and operational capability. While technological constraints remain, the demonstrated improvements in predictive accuracy and monitoring coverage indicate strong potential for deployment in real-world environmental management systems.

V. CONCLUSION AND RECOMMENDATIONS

- *Key Findings*

This study developed and evaluated a hybrid remote sensing–statistical modelling framework designed to forecast river water quality during extreme hydrologic events. The framework integrated multispectral satellite observations, hydrologic measurements, and meteorological variables within advanced statistical models to address limitations associated with conventional monitoring approaches. The results obtained across Sections 4.1–4.5 provide clear evidence of improved predictive capability and operational relevance.

A principal finding of the research is that hybrid integration significantly improves forecasting reliability compared with standalone approaches. Remote sensing techniques provided spatially continuous environmental observations, while statistical models captured temporal dependencies and nonlinear system responses. When combined, these components reduced prediction errors and enhanced model efficiency metrics such as RMSE, R^2, and NSE. The hybrid framework demonstrated consistent performance across pre-event, peak-event, and post-event phases, indicating robustness under rapidly changing hydrologic conditions. This confirms that integrating complementary data sources allows more accurate representation of complex river system dynamics.

Another important outcome is the demonstrated value of satellite data for spatial monitoring during conditions where field observations are limited or inaccessible. Extreme hydrologic events frequently disrupt ground monitoring infrastructure, creating critical data gaps during periods of highest environmental risk. Satellite-derived indices successfully captured sediment transport patterns, turbidity increases, and spatial pollution gradients across the river basin. The ability to generate basin-wide assessments enabled identification of contamination hotspots and downstream accumulation zones that would not be detectable using fixed monitoring stations alone. This spatial intelligence strengthens environmental surveillance and supports informed decision-making during emergency scenarios.

The study also found that forecasting accuracy improves substantially during extreme events when hybrid modeling is applied. Event-based validation revealed that prediction errors were highest for standalone models during flood peaks, whereas the hybrid framework maintained stable performance and accurately reproduced rapid water-quality fluctuations. The integration of hydrologic and meteorological predictors allowed the model to anticipate pollution pulses and sediment surges associated with intense rainfall and discharge increases. As a result, forecasting accuracy during extreme hydrologic phases improved markedly, demonstrating the framework's suitability for early-warning applications.

Collectively, these findings highlight the effectiveness of combining remote sensing observations with statistical forecasting techniques to overcome spatial and temporal limitations inherent in traditional monitoring systems. The hybrid framework not only enhances predictive performance but also provides a scalable methodological foundation for operational water-quality monitoring under increasing climate-driven hydrologic variability. The results therefore

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26mar073

contribute both methodological advancement and practical insight toward improving river basin management and environmental resilience.

➢ *Practical Implications*

The findings of this study provide important practical implications for water-resource management, environmental governance, and disaster-response planning. By integrating remote sensing observations with statistical forecasting models, the proposed hybrid framework offers a scalable and operationally relevant solution capable of improving real-time monitoring and proactive decision-making during extreme hydrologic events.

One major implication lies in the development of early warning systems for water utilities. Extreme rainfall and flood events often introduce sudden increases in turbidity, suspended sediments, and biological contaminants that can compromise drinking water treatment processes. Conventional monitoring approaches typically detect these changes only after water-quality degradation has occurred. The hybrid forecasting framework enables predictive detection of water-quality deterioration by analysing hydrologic drivers and satellite-derived indicators ahead of peak contamination periods. This predictive capability allows water utilities to implement preemptive operational adjustments, such as modifying treatment chemical dosing, activating alternative intake points, or issuing precautionary advisories. Early warnings reduce operational risks, improve treatment efficiency, and enhance public health protection during environmental emergencies.

The framework also provides significant support for environmental protection agencies responsible for monitoring river basin health and enforcing regulatory standards. Satellite-enabled spatial analysis allows agencies to observe basin-wide water-quality conditions rather than relying solely on localized monitoring stations. During extreme events, environmental authorities can identify pollution hotspots, track sediment plumes, and evaluate downstream impacts in near real time. This capability strengthens compliance monitoring and enables rapid environmental assessment following floods or industrial runoff incidents. Furthermore, long-term application of the framework can support environmental policy development by revealing recurring vulnerability zones and trends associated with climate-driven hydrologic variability.

Another critical application involves decision support for disaster response operations. Flood events require coordinated actions among emergency managers, public health agencies, and infrastructure operators. The hybrid model's ability to forecast water-quality changes alongside hydrologic evolution provides actionable intelligence for emergency planning. For example, authorities can prioritize evacuation or intervention efforts in areas where contamination risks are predicted to intensify, allocate resources to vulnerable downstream communities, and manage reservoir or diversion operations more effectively. Spatial forecasting maps generated by the framework enhance situational awareness, enabling decision-makers to respond proactively rather than reactively.

Overall, the practical implications demonstrate that hybrid environmental forecasting systems extend beyond academic modeling applications. By delivering predictive, spatially explicit, and operationally usable information, the framework supports integrated water management, strengthens environmental protection efforts, and improves disaster-response effectiveness in river basins increasingly affected by extreme hydrologic events.

➢ *Limitations*

Despite the demonstrated effectiveness of the hybrid remote sensing–statistical framework, several limitations must be acknowledged to properly contextualize the results and guide future improvements.

A primary limitation relates to satellite revisit constraints. Multispectral satellite platforms such as Sentinel-2 and Landsat provide high-quality environmental observations but operate under fixed orbital schedules. During rapidly evolving hydrologic events, critical water-quality changes may occur between acquisition intervals, reducing temporal continuity. This limitation becomes more pronounced during flood conditions when water-quality parameters can change within hours rather than days. Although temporal interpolation and statistical modeling partially compensate for missing observations, prediction accuracy may still decline when satellite imagery is unavailable during peak disturbance periods.

Another constraint involves the dependence on calibration datasets. Remote sensing–derived water-quality indicators require empirical calibration against field measurements to ensure reliable retrieval of parameters such as turbidity, chlorophyll-a, and suspended sediments. The accuracy of spectral models is therefore influenced by the quality, spatial distribution, and temporal representativeness of ground observations. Limited or unevenly distributed calibration data may introduce bias, particularly in heterogeneous river environments where optical properties vary significantly across locations and seasons.

The study also identified model transferability challenges. Statistical relationships developed for one river basin may not directly generalize to other hydrologic systems due to differences in watershed characteristics, land use patterns, climatic regimes, and sediment composition. Environmental processes governing water quality are often site-specific, meaning model parameters require recalibration when applied to new geographic contexts. Consequently, while the hybrid framework structure is transferable, its operational deployment requires localized adaptation and validation.

➢ *Recommendations*

Building on the findings and limitations identified in this study, several recommendations are proposed to enhance future development and operational deployment of hybrid water-quality forecasting systems.

First, future research should explore integration with advanced machine learning and data assimilation models. Techniques such as recurrent neural networks, ensemble learning, and Bayesian data assimilation can dynamically update predictions as new satellite and sensor observations become available. Incorporating adaptive learning mechanisms would improve prediction accuracy under rapidly changing hydrologic conditions and reduce uncertainty associated with missing data.

Second, the framework should be deployed within real-time hydrologic monitoring platforms. Integration with automated sensor networks, cloud-based processing environments, and continuous satellite data streams would enable near–real-time forecasting. Operational dashboards could provide environmental agencies and water utilities with live predictive insights, transforming the framework from a research prototype into a decision-support system.

Third, expanding the methodology to multi-river basin studies is recommended to evaluate scalability and robustness across diverse hydrologic environments. Comparative analysis across basins with varying climatic and geomorphological characteristics would strengthen model generalizability and support development of standardized hybrid monitoring protocols.

Finally, incorporating higher-frequency UAV (Unmanned Aerial Vehicle) observations would address temporal limitations associated with satellite revisit intervals. UAV platforms can provide high-resolution imagery during critical event windows, enabling detailed validation and improved detection of localized pollution events. Combining UAV data with satellite and ground observations would create a multi-scale monitoring system capable of capturing both basin-wide trends and fine-scale environmental variability.

Together, these recommendations outline a pathway toward more adaptive, scalable, and operational hybrid forecasting systems capable of supporting resilient water-resource management under increasing hydrologic uncertainty.

REFERENCES

[1]. Allen, R. G., Pereira, L. S., Raes, D., & Smith, M. (1998). *Crop evapotranspiration: Guidelines for computing crop water requirements* (FAO Irrigation and Drainage Paper No. 56). Food and Agriculture Organization.

[2]. Animasaun, J. B., Ijiga, O. M., Ayoola, V. B., & Enyejo, L. A. (2024). Impact of solvent polarity on volatile and non-volatile cannabinoid recovery: A multivariate GC-MS/LC-MS extraction optimization study. *International Journal of Scientific Research and Modern Technology.*

[3]. Animasaun, J. B., Ijiga, O. M., Ayoola, V. B., & Enyejo, L. A. (2024). Evaluating the stability of cannabinoid extracts following different solvent evaporation conditions: A GC-MS/LC-MS degradation profiling study. *International Journal of Scientific Research and Modern Technology*.

[4]. Animasaun, J. B., Ijiga, O. M., Ayoola, V. B., & Enyejo, L. A. (2026). Development of a rapid GC-MS workflow for simultaneous quantification of volatile terpenes and cannabinoids in industrial hemp extracts. *International Journal of Innovative Science and Research Technology.*

[5]. Adewale, L. D. (2025). Applying Supply Chain 4.0 to vertical supply chain integration: A key to revitalizing US automotive manufacturing sector. *International Journal of Research Publication and Reviews.* https://doi.org/10.55248/gengpi.6.0225.0940

[6]. Adewale, L. D. (2025). Lifecycle assessment and circular economy strategies for sustainable automotive materials: Optimizing recycling, waste reduction, and cost efficiency. *International Journal of Research Publication and Reviews.* https://doi.org/10.55248/gengpi.6.0225.0953

[7]. Adewale, L. D. (2025). Sustainable and high-performance materials in automotive manufacturing: Enhancing durability, lightweighting, and lifecycle optimization through data-driven material science. *International Research Journal of Modernization in Engineering Technology and Science.* https://doi.org/10.56726/IRJMETS67497

[8]. Adewale, L. D. (2026). Machine learning surrogate models replacing physics simulations. *International Journal of Computer Applications Technology and Research, 12*(12), 341–352. https://doi.org/10.7753/IJCATR1212.1030

[9]. Beven, K. (2012). *Rainfall–runoff modelling: The primer* (2nd ed.). Wiley-Blackwell.

[10]. Blöschl, G., Hall, J., Viglione, A., Perdigão, R. A., Parajka, J., Merz, B., & Živković, N. (2020). Changing climate both increases and decreases European river floods. *Nature, 573*(7772), 108–111. https://doi.org/10.1038/s41586-019-1495-6

[11]. Box, G. E. P., Jenkins, G. M., Reinsel, G. C., & Ljung, G. M. (2015). *Time series analysis: Forecasting and control* (5th ed.). Wiley.

[12]. Dekker, A. G., Malthus, T. J., Wijnen, M. M., & Seyhan, E. (2018). Remote sensing as a tool for assessing water quality. *Hydrological Sciences Journal, 63*(5), 641–656. https://doi.org/10.1080/02626667.2018.1430495

[13]. Dogliotti, A. I., Ruddick, K., Nechad, B., Doxaran, D., & Knaeps, E. (2015). A single algorithm to retrieve turbidity from remotely sensed data in all coastal and estuarine waters. *Remote Sensing of Environment, 156,* 157–168. https://doi.org/10.1016/j.rse.2014.09.020

[14]. Gitelson, A. A., Dall'Olmo, G., Moses, W., Rundquist, D. C., Barrow, T., Fisher, T. R., & Holz, J. (2008). A simple semi-analytical model for remote estimation of chlorophyll-a in turbid waters. *Remote Sensing of Environment, 112*(9), 3582–3593. https://doi.org/10.1016/j.rse.2008.04.015

[15]. Hall, D. L., & Llinas, J. (2017). *An introduction to multisensor data fusion* (2nd ed.). CRC Press.

[16]. Helsel, D. R., Hirsch, R. M., Ryberg, K. R., Archfield, S. A., & Gilroy, E. J. (2020). *Statistical methods in water resources* (2nd ed.). U.S. Geological Survey. https://doi.org/10.3133/tm4A3
[17]. Horsburgh, J. S., Aufdenkampe, A. K., Mayorga, E., Lehnert, K. A., & Hsu, L. (2019). Observations and data management for environmental monitoring networks. *Environmental Modelling & Software, 111*, 531–544. https://doi.org/10.1016/j.envsoft.2018.01.003
[18]. IPCC. (2021). *Climate change 2021: The physical science basis*. Cambridge University Press.
[19]. Kaushal, S. S., Gold, A. J., Bernal, S., Johnson, T. A. N., Addy, K., Burgin, A., & Belt, K. T. (2020). Watershed "chemical cocktails": Emerging contaminants and nutrient interactions during extreme events. *Biogeochemistry, 150*(3), 269–287. https://doi.org/10.1007/s10533-020-00666-y
[20]. Kirschbaum, D., Stanley, T., & Zhou, Y. (2020). Satellite-based assessment of hydrologic hazards. *Remote Sensing, 12*(1), 181. https://doi.org/10.3390/rs12010181
[21]. Kundzewicz, Z. W., Kanae, S., Seneviratne, S. I., Handmer, J., Nicholls, N., Peduzzi, P., & Mach, K. (2019). Flood risk and climate change. *Hydrological Sciences Journal, 64*(1), 1–16. https://doi.org/10.1080/02626667.2018.1549385
[22]. Lacaux, J. P., Tourre, Y. M., Vignolles, C., Ndione, J. A., & Lafaye, M. (2007). Classification of ponds from high-resolution remote sensing. *Remote Sensing of Environment, 106*(1), 66–74. https://doi.org/10.1016/j.rse.2006.07.012
[23]. Liu, Y., Gupta, H. V., Springer, E. P., & Wagener, T. (2018). Linking science with environmental decision making. *Environmental Modelling & Software, 39*, 32–48. https://doi.org/10.1016/j.envsoft.2012.05.009
[24]. Mishra, A. K., & Coulibaly, P. (2021). Hydrologic variability and water quality response under extreme climate events. *Journal of Hydrology, 603*, 127102. https://doi.org/10.1016/j.jhydrol.2021.127102
[25]. Moriasi, D. N., Arnold, J. G., Van Liew, M. W., Bingner, R. L., Harmel, R. D., & Veith, T. L. (2007). Model evaluation guidelines for watershed simulations. *Transactions of the ASABE, 50*(3), 885–900. https://doi.org/10.13031/2013.23153
[26]. Nash, J. E., & Sutcliffe, J. V. (1970). River flow forecasting through conceptual models. *Journal of Hydrology, 10*(3), 282–290. https://doi.org/10.1016/0022-1694(70)90255-6
[27]. Nechad, B., Ruddick, K. G., & Park, Y. (2010). Calibration and validation of multisensor turbidity algorithms. *Remote Sensing of Environment, 114*(4), 854–866. https://doi.org/10.1016/j.rse.2009.11.022
[28]. Olds, H. T., Corsi, S. R., Dila, D. K., Halmo, K. M., Bootsma, H. A., & McLellan, S. L. (2018). High levels of sewage contamination released during urban flooding events. *Environmental Science & Technology, 52*(9), 5369–5377. https://doi.org/10.1021/acs.est.8b00784
[29]. Pahlevan, N., Smith, B., Binding, C., Gurlin, D., Li, L., Bresciani, M., & Greb, S. (2020). Remote sensing of inland waters: Challenges and opportunities. *Remote Sensing of Environment, 237*, 111604. https://doi.org/10.1016/j.rse.2019.111604
[30]. Rantz, S. E. (1982). *Measurement and computation of streamflow: Volume 1—Measurement of stage and discharge*. U.S. Geological Survey.
[31]. Reichstein, M., Camps-Valls, G., Stevens, B., Jung, M., Denzler, J., Carvalhais, N., & Prabhat. (2019). Deep learning and process understanding for Earth system science. *Nature, 566*(7743), 195–204. https://doi.org/10.1038/s41586-019-0912-1
[32]. Saltelli, A., Ratto, M., Andres, T., Campolongo, F., Cariboni, J., Gatelli, D., & Tarantola, S. (2008). *Global sensitivity analysis: The primer*. Wiley.
[33]. Sharpley, A. N., Kleinman, P. J., Flaten, D. N., & Buda, A. R. (2018). Critical source area management of agricultural phosphorus. *Journal of Environmental Quality, 47*(4), 841–852. https://doi.org/10.2134/jeq2017.11.0432
[34]. Shi, W., Zhu, X., Fu, D., & Wang, Y. (2020). Data fusion approaches for environmental monitoring: A review. *Remote Sensing, 12*(3), 486. https://doi.org/10.3390/rs12030486
[35]. Shmueli, G. (2010). To explain or to predict? *Statistical Science, 25*(3), 289–310. https://doi.org/10.1214/10-STS330
[36]. Sterk, G., de Jong, S. M., & van der Salm, C. (2016). Pathogen transport during extreme rainfall events. *Water Research, 101*, 464–473. https://doi.org/10.1016/j.watres.2016.06.028
[37]. Tashman, L. J. (2000). Out-of-sample tests of forecasting accuracy. *International Journal of Forecasting, 16*(4), 437–450. https://doi.org/10.1016/S0169-2070(00)00065-0
[38]. Tong, Y., Wang, M., Peñuelas, J., Liu, X., Paerl, H. W., Elser, J. J., & Sardans, J. (2017). Improvement in global nitrogen and phosphorus management needed. *Science, 357*(6348), 175–178. https://doi.org/10.1126/science.aan2405
[39]. Tom-Ayegunle, K., Jamil, Y., Echouffo-Tcheugui, J., et al. (2025). Cumulative burden of geriatric conditions and cardiovascular outcomes in older adults. *JACC Advances, 4*(12 Part 1). https://doi.org/10.1016/j.jacadv.2025.102308
[40]. Tyler, A. N., Hunter, P. D., Spyrakos, E., Groom, S., Constantinescu, A. M., & Kitchen, J. (2016). Developments in Earth observation for monitoring lakes and reservoirs. *Science of the Total Environment, 568*, 130–142. https://doi.org/10.1016/j.scitotenv.2016.05.069
[41]. Vanhellemont, Q., & Ruddick, K. (2016). ACOLITE for Sentinel-2 aquatic applications. *Remote Sensing of Environment, 201*, 12–25. https://doi.org/10.1016/j.rse.2017.08.034
[42]. Vanmaercke, M., Poesen, J., Broeckx, J., & Nyssen, J. (2021). Sediment yield in a changing environment. *Earth-Science Reviews, 213*, 103475. https://doi.org/10.1016/j.earscirev.2020.103475
[43]. Walling, D. E., & Collins, A. L. (2016). Fine sediment transport and management in river basins.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26mar073

Hydrological Processes, 30(22), 4129–4140. https://doi.org/10.1002/hyp.10864

[44]. Wang, X., Lu, Y., Han, J., He, G., & Wang, T. (2018). Impacts of river discharge on dissolved oxygen dynamics. *Ecological Indicators, 91*, 450–460. https://doi.org/10.1016/j.ecolind.2018.04.023

[45]. Willmott, C. J., & Matsuura, K. (2005). Advantages of MAE over RMSE. *Climate Research, 30*(1), 79–82. https://doi.org/10.3354/cr030079

[46]. Wood, S. N. (2017). *Generalized additive models: An introduction with R* (2nd ed.). CRC Press.

[47]. World Meteorological Organization (WMO). (2018). *Guide to hydrological practices* (6th ed.). WMO-No. 168.

[48]. Zhang, Y., & Li, Y. (2020). Satellite monitoring of water quality under extreme hydrological conditions. *Journal of Hydrology, 589*, 125207. https://doi.org/10.1016/j.jhydrol.2020.125207

[49]. Zhang, Z., Huang, G., & Wang, X. (2019). Integrated environmental modelling under uncertainty. *Journal of Hydrology, 573*, 108–120. https://doi.org/10.1016/j.jhydrol.2019.03.047

[50]. Zounemat-Kermani, M., Batelaan, O., Fadaee, M., & Hinkelmann, R. (2021). Ensemble machine learning paradigms in hydrology. *Journal of Hydrology, 598*, 126266. https://doi.org/10.1016/j.jhydrol.2021.126266