

A PHYSICS-ML APPROACH FOR RESOLVING MORPHODYNAMIC INSTABILITIES IN HIGHLY REGULATED RIVER BASINS

UNE APPROCHE ALLIANT PHYSIQUE ET APPRENTISSAGE AUTOMATIQUE POUR RÉSOUDRE LES INSTABILITÉS MORPHODYNAMIQUES DANS LES BASSINS VERSANTS FORTEMENT RÉGULÉS

Sentani¹, S.I. Wahyudi², M. Mukhlisin³ and F.C Boogaard⁴

ABSTRACT

The Tuntang Watershed in Central Java, Indonesia, faces severe socio-ecological crises driven by rapid morphological transformation and anthropogenic land-use changes. Extreme topographic disparities—from steep, highly erodible volcanic headwaters to ultra-low gradient alluvial plains in Demak—create a polarized hazard landscape characterized by massive upstream sediment flux and devastating downstream floods. Concurrently, the governance of Lake Rawa Pening, the basin's primary regulatory node, is paralyzed by entrenched water-use conflicts among state hydroelectric operators, agriculturalists, and riparian communities. To resolve these multidimensional challenges, this research proposes a real-time digital twin framework deployed via the RIVANA cloud platform. This architecture surpasses traditional empirical models by integrating Physics-Informed Machine Learning (PIML). Specifically, it utilizes a Deep Neural Network (DNN) initialized via the empirical Universal Soil Loss Equation $A = R \times K \times LS \times C \times P$ and enhanced with dynamic hydro-meteorological variables to accurately predict suspended sediment, bedload, and deposition rates. Furthermore, the system employs Physics-Informed Neural Networks (PINNs) to solve the coupled 1D and 2D Saint-Venant and Exner equations, strictly enforcing mass and momentum conservation. The PINN models demonstrate extraordinary computational efficiency, generating sub-grid inundation and sediment transport forecasts in 5 to 10 seconds with high accuracy. By encapsulating this advanced predictive engine within a universally accessible Application Programming Interface, the RIVANA framework democratizes hydrological intelligence. This transparency mathematically mediates stakeholder conflicts by replacing subjective demands with objective impact projections. Ultimately, this scalable digital infrastructure provides the rigorous, verifiable metrics necessary to sustain Payment for Environmental Services (PES) paradigms, fostering equitable watershed governance and long-term socio-ecological resilience.

Keywords: multidimensional challenges traditional empirical models; hydrological intelligence; socio-ecological resilience.

RESUME

Le bassin versant de Tuntang, situé au centre de Java en Indonésie, est confronté à de graves crises socio-écologiques provoquées par une transformation morphologique rapide et des changements anthropiques d'usages des sols. Des disparités topographiques extrêmes — des eaux d'amont volcaniques abruptes et très érosives aux plaines alluviales à très faible pente de Demak — créent un paysage de risque polarisé caractérisé par d'importants flux de sédiments en amont et des inondations dévastatrices en aval. Parallèlement, la gouvernance du lac Rawa Pening, le principal nœud de régulation du bassin, est paralysée par des conflits enracinés sur l'utilisation de l'eau entre les opérateurs hydroélectriques d'État, les agriculteurs et les communautés riveraines. Pour résoudre ces

¹ Universitas Islam Sultan Agung, Civil Engineering, Semarang, Indonesia Email: arisentani@unissula.ac.id

² Universitas Islam Sultan Agung, Civil Engineering, Semarang, Indonesia Email: wahyudi@unissula.ac.id

³ Politeknik Negeri Semarang, Civil Engineering, Semarang, Indonesia Email: mmukhlis@polines.ac.id

⁴ Hanze University of Applied Sciences, Civil Engineering, Groningen, Netherlands Email: f.c.boogaard@pl.hanze.nl

défis multidimensionnels, cette recherche propose un cadre de jumeau numérique en temps réel déployé via la plateforme cloud RIVANA. Cette architecture surpasse les modèles empiriques traditionnels en intégrant l'apprentissage automatique basé sur la physique (PIML). Plus précisément, il utilise un réseau de neurones profonds (DNN) initialisé via l'équation empirique universelle de perte de sol $A = R \times K \times LS \times C \times P$ et amélioré avec des variables hydrométéorologiques dynamiques pour prédire avec précision les sédiments en suspension, le charriage et les taux de dépôt. De plus, le système utilise des réseaux de neurones informés par la physique (PINN) pour résoudre les équations couplées 1D et 2D de Saint-Venant et d'Exner, en appliquant strictement la conservation de la masse et du moment. Les modèles PINN démontrent une efficacité de calcul remarquable, générant des prévisions d'inondation et de transport de sédiments en 5 à 10 secondes avec une grande précision. En intégrant ce moteur prédictif avancé dans une interface de programmation d'application (API) accessible à tous, le cadre RIVANA démocratise l'intelligence hydrologique. Cette transparence permet de résoudre mathématiquement les conflits entre parties prenantes en remplaçant les exigences subjectives par des projections d'impact objectives. En fin de compte, cette infrastructure numérique évolutive fournit les mesures rigoureuses et vérifiables nécessaires pour soutenir les paradigmes de paiement pour services environnementaux (PSE), favorisant une gouvernance équitable des bassins versants et une résistance socio-écologique à long terme.

Mots-clés : Défis multidimensionnels; Modèles empiriques traditionnels; Intelligence hydrologique; Résistance socio-écologique.

INTRODUCTION

Tropical river basins are among the systems most exposed to the compounding pressures of climate change and rapid land-use conversion. Intensifying rainfall, accelerating urbanization and agricultural expansion jointly degrade the natural retention capacity of catchments, amplifying surface runoff, soil erosion and downstream flood risk (Xu et al., 2025). In sediment-dominated basins the hazard is not driven by discharge alone: eroded upland material is transported downstream and progressively aggrades the channel, reducing hydraulic conveyance and exposing low-gradient floodplains to recurrent, catastrophic inundation. Tropical river basins are among the systems most exposed to the compounding pressures of climate change and rapid land-use conversion. Intensifying rainfall, accelerating urbanization, and agricultural expansion jointly degrade the natural retention capacity of catchments, amplifying surface runoff, soil erosion, and downstream flood risk (Blöschl et al., 2019). The Tuntang Watershed in Central Java, Indonesia, serves as an archetypal example of this multidimensional socio-ecological crisis. Spanning approximately 799.3 km² and acting as a vital ecological and socio-economic pillar for the national strategic area of Kedungsepur, the basin's hydrology is historically regulated by Lake Rawa Pening—a critical 250.79 km² natural reservoir with an initial storage capacity of 65 million m³. Draining roughly 139 km from volcanic headwaters around Mounts Merbabu and Ungaran to the Java Sea, which directly into an ultra-low-gradient alluvial coastal plain sitting merely 3 meters above sea level, the basin exhibits an extreme "steep-to-flat" morphological anomaly (Syvitski et al., 2022). This topography intrinsically predisposes the region to severe hydrological stress. Intensifying meteorological triggers, notably maximum daily rainfalls of 50–64 mm, generate sudden peak flows reaching up to 800 m³/s.

Field and remote-sensing studies report a predominantly meandering, laterally migrating channel, with severe and continuous erosion concentrated in the Rowopening and Senjoyo sub-watersheds. The basin therefore couples a physical instability (flood-generating channel aggradation) with a governance failure (zero-sum competition over water allocation under deep information asymmetry), and neither can be resolved in isolation from the other. As a highly dynamic tropical river basin currently undergoing rapid and destructive morphological transformation, the Tuntang Watershed serves as an archetypal model of the multidimensional socio-ecological crises facing modern hydrology. Anthropogenic land-use alterations, driven by relentless urbanization and the expansion of high-intensity agriculture, have fundamentally degraded the basin's natural retention capacity. This degradation has subsequently intensified surface runoff, accelerated catastrophic soil erosion, and drastically altered the river's fundamental morphodynamics, thereby severely amplifying downstream flood vulnerability. Recent

fluvial morpho dynamic studies extensively document how relentless anthropogenic pressures—specifically urbanization and high-intensity agricultural expansion—exacerbate lateral channel migration, upstream erosion, and downstream flood vulnerability in highly regulated basins (Ielpi et al., 2023; Xie et al., 2022). However, contemporary socio-hydrological literature emphasizes that these physical instabilities cannot be resolved in isolation, as they are intrinsically coupled with the power dynamics and socio-economic architectures that govern them (Rusca & Di Baldassarre, 2022). Stakeholders operating within these degraded catchments often find themselves locked in zero-sum competitions over water allocation and resource management, exacerbated by deep information asymmetry and fragmented institutional cooperation (Wei et al., 2022).

Despite the consensus on this socio-ecological coupling, current predictive paradigms remain methodologically inadequate for dynamic policy integration. Traditional hydrodynamic solvers are computationally prohibitive for real-time institutional forecasting, while purely socio-economic frameworks lack robust, physics-constrained validation. To bridge this critical gap, recent advancements in Physics-Informed Machine Learning (PIML)—specifically Physics-Informed Neural Networks (PINNs) engineered to solve complex non-linear equations like Saint-Venant and Exner—offer a transformative, computationally efficient alternative (Karniadakis et al., 2021). By synthesizing PINNs into a scalable, API-driven Digital Twin, this research proposes a novel epistemological shift that provides highly transparent, sub-grid resolution predictions of flood routing and sediment transport. This technological integration acts as a proactive governance mechanism, dissolving information asymmetry and enabling the precise operationalization of progressive economic interventions, such as verifiable Payment for Environmental Services (PES) (Börner et al., 2020).

Anthropogenic land-use alterations have severely exacerbated upland erosion and downstream channel aggradation, rendering existing flood infrastructure inadequate and exposing a critical lack of real-time predictive models. To resolve these compounding physical and institutional failures, this study develops a computationally efficient, real-time predictive modeling framework by synthesizing Physics-Informed Neural Networks (PINNs) to solve the complex Saint-Venant and Exner equations (Karniadakis et al., 2021) within an API-driven digital twin. Overcoming the prohibitive computational costs of traditional hydrodynamic solvers, this physics-constrained approach captures the non-linear dynamics of flood-generating channel aggradation and serves as a proactive governance mechanism to facilitate equitable dispute resolution and operationalize progressive economic strategies, such as Payment for Environmental Services (Wunder et al., 2018).

RESEARCH METHODOLOGY

This study proposes a highly integrated computational framework named RIVANA (River Analysis with Validated Neural Architecture). This system couples high-resolution satellite data with Physics-Informed Machine Learning (PIML) to establish a real-time hydrological Digital Twin. The methodology is executed through three primary stages: automated Application Programming Interface (API)-based data acquisition, hydrometeorological parameter reprocessing, and predictive modelling based on artificial neural networks (ANN) constrained by physical laws.

System Architecture and Geospatial Data Acquisition

To overcome the constraints of field data scarcity and information asymmetry in the Tuntang Watershed, data collection is automated using the Google Earth Engine (GEE) cloud computing infrastructure. The system architecture is built using the Python programming language, where communication between the local environment (Python) and the GEE server is bridged by a secret key (API credential). This access code acts as an authenticator enabling the Python script to execute spatial and temporal queries directly to Google's satellite database. To optimize computational efficiency and minimize API quota usage, the system employs a Batch Processing method. Simulation coordinate points—representing the upstream zone on the slopes of Mounts Merbabu and Ungaran down to the downstream area in the Demak and Grobogan regencies—along with simulation time intervals are inputted through the Python interface. The system then extracts multiple datasets in a single API call, generating raw datasets (CSV)

and metadata (JSON) simultaneously. The acquired geospatial data includes: (1) Precipitation: CHIRPS Daily data (5.5 km resolution), (2) Air Temperature: ERA5-Land (11 km resolution), (3) Soil Moisture: SMAP (10 km resolution), (4) Vegetation Index (NDVI): MODIS (250 m resolution), and (5) Morphology (Elevation and Slope): SRTM DEM (30 m resolution).

Preprocessing and ML-Based Evapotranspiration Estimation

The raw data extracted from GEE undergoes rigorous data cleaning and temporal interpolation, particularly for 16-day interval data such as NDVI. Subsequently, these baseline features are fed into an initial Deep Neural Network (DNN) to estimate Evapotranspiration (ET). Unlike traditional empirical equations (such as the Penman-Monteith method) that require dozens of field meteorological parameters, this ET extraction model is trained using limited satellite parameters (temperature, NDVI, precipitation, and soil moisture) but is bootstrapped against pure physical equations. This approach generates a robust derived evapotranspiration variable with high accuracy, which is essential for subsequent water balance calculations.

Physics-Informed Neural Networks (PINNs) Formulation

The core of this system's predictive framework is the Physics-Informed Deep Neural Network (PI-DNN) architecture. Unlike conventional machine learning models that operate purely as data-driven "black boxes," the PI-DNN integrates hydromorphological laws—specifically the Saint-Venant and Exner equations—directly into the neural network's loss function. This ensures that predictions for surface runoff, infiltration, baseflow, and sediment transport strictly adhere to the physical principles of mass conservation.

The system validates the law of mass conservation using the fundamental Water Balance equation:

$$P = ET + R + I + \Delta S + \varepsilon$$

Where P is precipitation, ET is evapotranspiration, R is surface runoff, I is infiltration, ΔS is the change in water storage, and ε is the residual error, which must approach zero. During the training process, the neural network—utilizing a Bidirectional LSTM architecture to capture the extreme temporal dependencies of weather anomalies—is trained by evaluating a hybrid loss function L :

$$L = L_{MSE} + \lambda_1 L_{mass} + \lambda_2 L_{neg} + \lambda_3 L_{phys}$$

In this formulation, L_{mass} is the data-driven prediction error (Mean Squared Error), L_{mass} is the penalty for water mass balance violations, L_{neg} is the non-negativity penalty (ensuring volume and discharge values are strictly non-negative), and L_{phys} represents additional physical constraints. The λ parameters serve as adaptive weights for the physics penalties.

RESULT

Spatial, Geological, and Morphodynamic Topography of the Tuntang Basin

The Tuntang Watershed is characterized by extreme topographic heterogeneity (

Figure 1)., transitioning rapidly from low-lying, flat northern coastal plains (1–50 m elevation, 0–8% slopes) to rugged southern volcanic highlands exceeding 262 meters with slopes over 40%. These sharp gradient dictates runoff dynamics: the expansive northern terrain acts as a primary depositional zone with low river flow velocities, while the steep southern headwaters generate highly aggressive, erosive surface runoff during monsoon events.

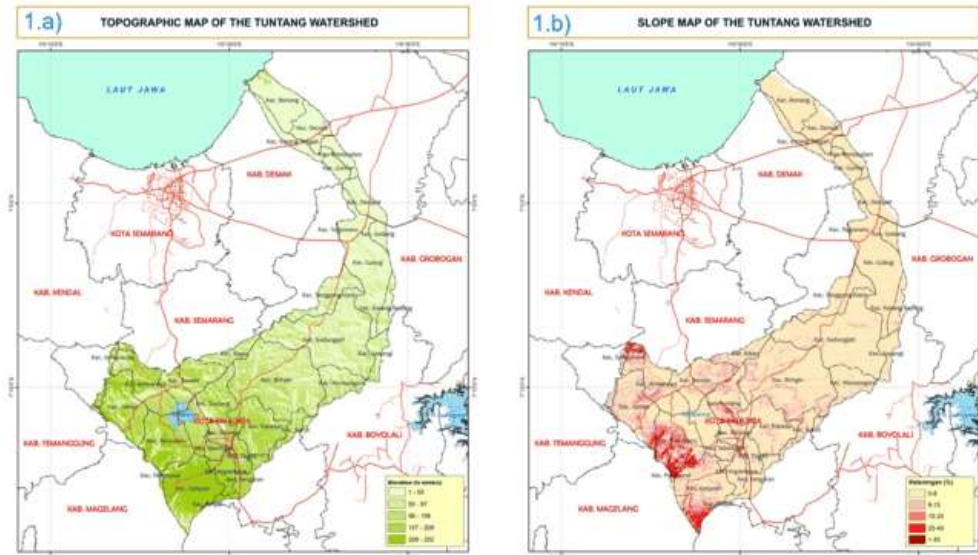


Figure 1. (a) Topographic map and (b) Slope map of Tuntang Watershed

Figure 2 shows the topographic of Tuntang Watershed that divide directly mirrors the basin's underlying geology and soil composition. The northern plains are overwhelmingly composed of Holocene alluvial deposits—constituting 95.64% of the Demak Regency—paired with fertile but structurally unconsolidated alluvial soils. Conversely, the central and southern regions shift to complex volcanic, sedimentary, and limestone facies, where the steep upper slopes are blanketed by Andosol and Latosol profiles. While highly productive for agriculture, these volcanic soils are notoriously susceptible to severe sheet erosion and mass waste when natural forest cover is stripped.

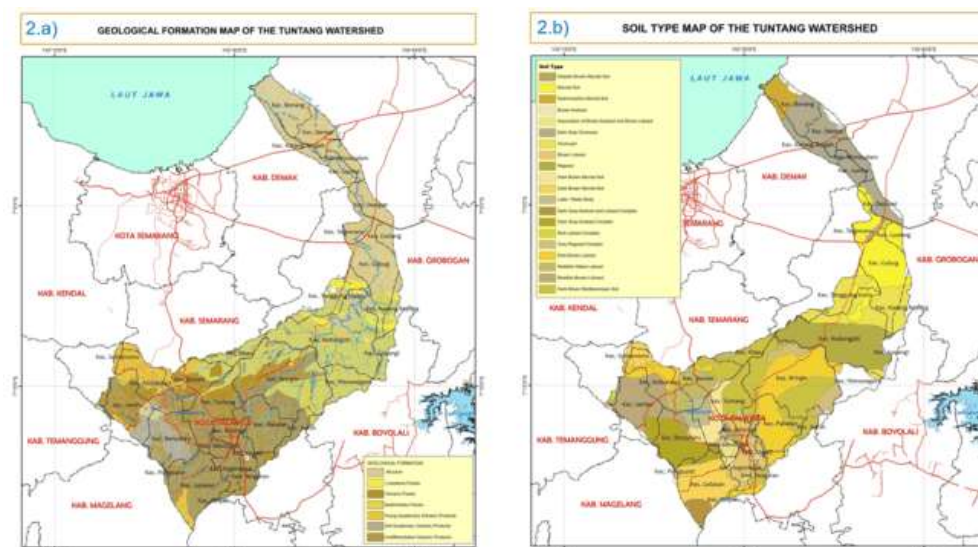


Figure 2. (a) Geological formation map and (b) Soil type map of Tuntang Watershed

Consequently, this intersection of topography and geology creates a highly polarized, interconnected hazard landscape across the watershed (Figure 3). Seismic risks escalate from moderate in the north to high along the central and southern fault lines, threatening critical water infrastructure like the Rawa Pening dam. On a hydrometeorological level, chronic flooding heavily impacts the poorly drained, low-gradient alluvial plains of Demak, whereas landslides are concentrated on the unstable, steep slopes of the southern sub-districts. Crucially, these hazards are systemically linked; intense precipitation triggers

upstream landslides that inject massive sediment pulses into the river network, which travel downstream to accelerate channel siltation and exponentially worsen flood risks in Demak.

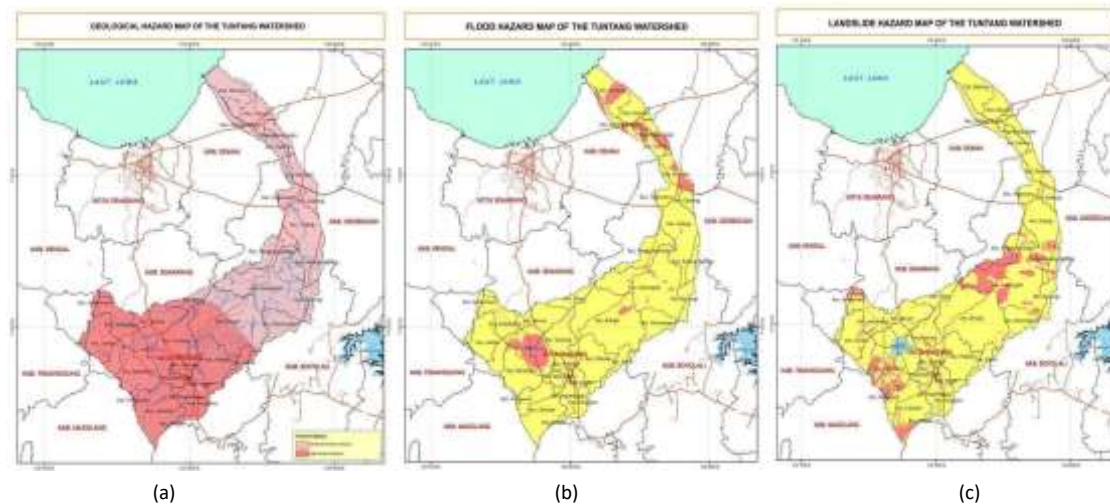


Figure 3. Hazard maps of Tuntang Watershed: (a) Geological hazard map, (b) Flood hazard maps and (c) Landslide map

Morphological Transformation and Sediment Dynamics Based on Revised Universal Soil Loss Equation (RUSLE)

The spatial distribution of the five primary parameters governing the Revised Universal Soil Loss Equation (RUSLE) within the study region is illustrated in

Figure 4. These layers were systematically processed and mapped using cloud-based geoprocessing within the Google Earth Engine (GEE) platform, which effectively accommodated multi-source satellite products and environmental reanalysis datasets at varying spatial resolutions.

Figure 4.(a) represented the Conservation Support Practice Factor (P), which accounts for localized erosion control structures and land management practices within the catchment area.

Figure 4.(b) delineated the Cover Management Factor (C), reflecting the mitigation of soil detachment provided by the vegetation canopy. This layer was computed using the Normalized Difference Vegetation Index (NDVI) derived from MODIS imagery at a 250 m spatial resolution to capture seasonal and spatial vegetative characteristics.

Figure 4.(c) represented the Slope Length and Steepness Factor (LS), representing the complex topographic influence on runoff acceleration and soil erosion potential.

This factor was explicitly derived from the SRTM Digital Elevation Model (DEM) at a high resolution of 30 m, allowing for precise identification of steep gradients and rugged terrains prone to high sediment yields.

Figure 4.(d) illustrates the Soil Erodibility Factor (K), mapping the inherent susceptibility of regional soil types to detachment and transport. The baseline soil dynamics within the computational framework are supported by the integration of SMAP soil moisture data (10 km resolution) and ERA5-Land air temperature reanalysis (11 km resolution) to account for hydro-meteorological influences on soil properties.

Figure 4.(e) captures the Rainfall Erosivity Factor (R), representing the kinetic energy and erosive potential of precipitation. This parameter was modeled using long-term daily precipitation records extracted from the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS Daily at a 5.5 km resolution).

Collectively, these GEE-derived spatial layers provide the foundational multi-parameter inputs required for the subsequent Deep Neural Network (DNN) architecture to predict comprehensive sediment transport dynamics.

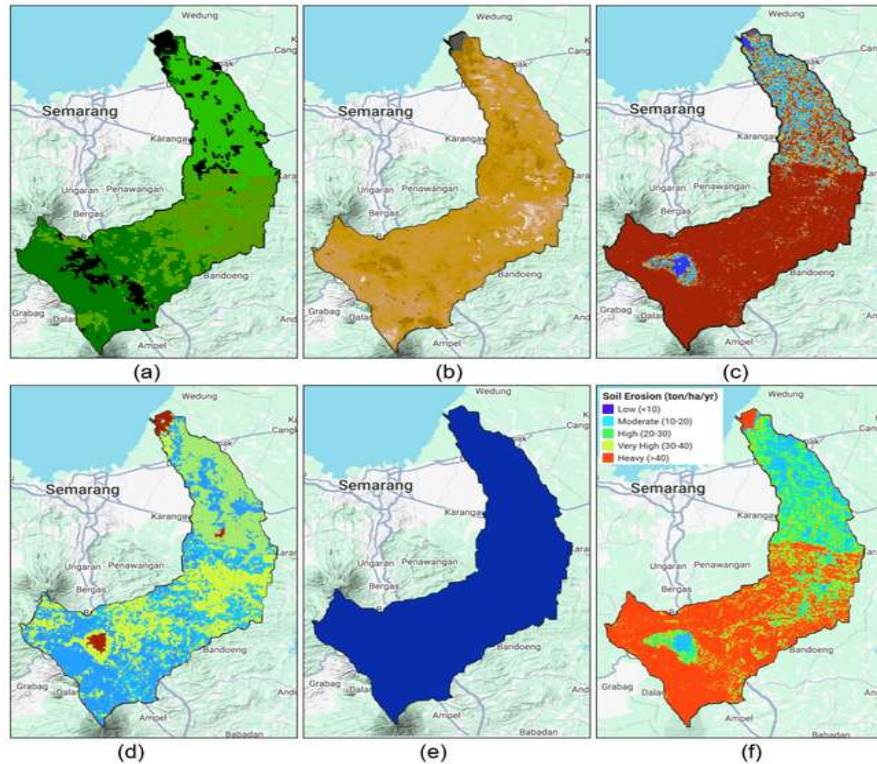


Figure 4. Spatial distribution maps of the Revised Universal Soil Loss Equation (RUSLE) factors generated via Google Earth Engine (GEE) (2021-2025): (a) conservation support practice factor (P), (b) cover management factor (C), (c) slope length and steepness factor (LS), (d) soil erodibility factor (K), (e) rainfall erosivity factor (R) and (f) Soil Erosion

Morphological Transformation and Sediment Dynamics Based RIVANA

Morphological Transformation and Sediment Dynamics modelling Based RIVANA to provide evaluation the reliability and spatial accuracy of the estimated sediment dynamics, the baseline layers generated via Google Earth Engine (GEE) were systematically cross-examined with the outputs produced by the RIVANA framework. This comparative analysis was executed across three strategic observation points selected to represent the complete hydrological continuum of the Tuntang Watershed: the upstream, midstream, and downstream reaches area. By assessing these distinct geographical zones, the integration of the Deep Neural Network (DNN) and machine learning (ML) enhancements within RIVANA could be rigorously validated against the empirical-remote sensing hybrid inputs across varying topographic and land-use gradients.

Table 1. Localized hydro-morphological and sediment characteristics across the Tuntang Watershed continuum extracted via RIVANA.

River Reach	Geographic Location and Coordinates	Sediment Load (ton/day)	Average Erosion (mm/year)
Upstream	Polosiri, Semarang Regency (-7.235095°, 110.493823°)	13.00	44.62
Midstream	Deras, Grobogan Regency (-7.156335°, 110.660742°)	8.40	33.24
Downstream	Kalikondang, Demak Regency (-6.917011°, 110.603055°)	5.75	30.85

Table 1 shows The Upstream Reach exhibits the highest vulnerability, characterized by an average erosion rate of 44.62 mm/year and a daily sediment load of 13.00 ton/day. This severe sediment yield is heavily influenced by steep topographic gradients and high kinetic energy from rainfall erosivity typical of the upper catchment zones. In the Midstream Reach, the average erosion rate attenuates to 33.24 mm/year, coinciding with a reduced sediment load of 8.40 ton/day. The Downstream Reach displays the lowest erosion rate (30.85 mm/year) and a minimized sediment load of 5.75 ton/day at this specific cross-section, reflecting the typical low-gradient energy dissipation and sediment deposition characteristics closer to the river mouth.

These localized point-source metrics strongly correlate with the macro-spatial soil erosion mapping generated via GEE

Figure 4.(f) wherein the upstream catchment is heavily dominated by red zones indicating heavy erosion (>40 ton/ha/yr). Concurrently, the geographical coordinates governing the midstream and downstream segments of the Tuntang Watershed predominantly transition into yellow clusters, which signify a very high erosion intensity (30–40 ton/ha/yr).

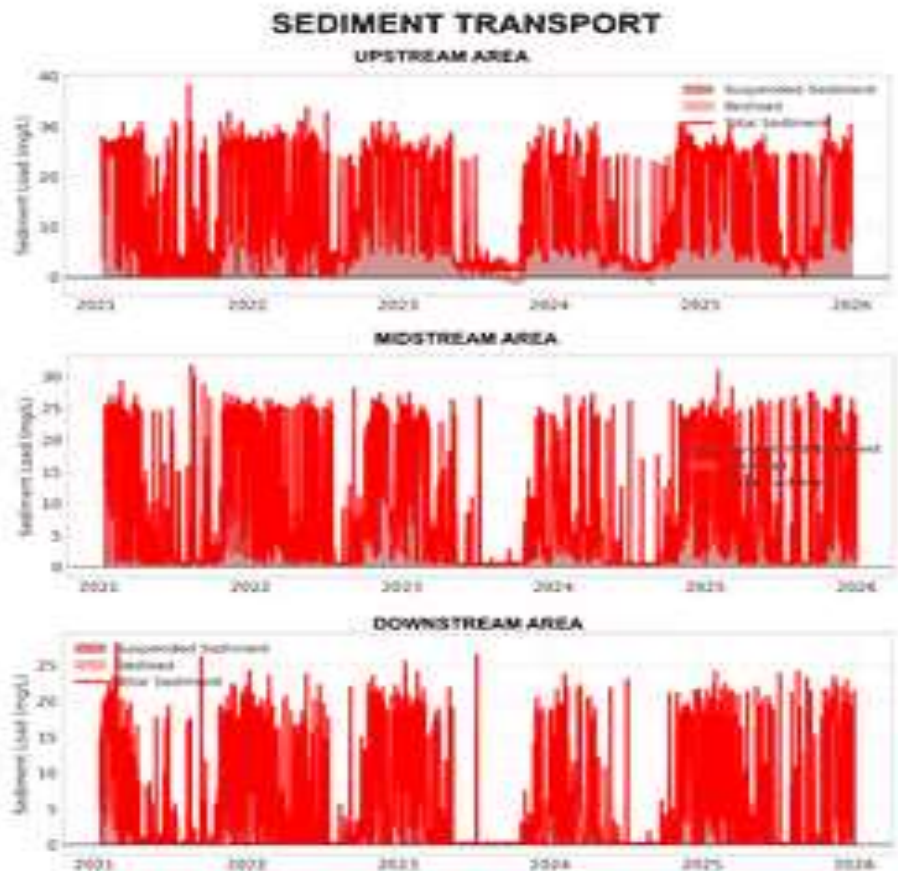


Figure 5. Sediment Transport Time Series (2021-2025) based RIVANA

DISCUSSION

The multidimensional crises facing the Tuntang Watershed—characterized by rapid morphological transformations, severe upstream erosion, and compounding socio-hydrological conflicts—create an environment of profound decision-making complexity. Traditional, fragmented approaches to water

management are structurally insufficient to address the highly non-linear dynamics of flood-generating channel aggradation or to resolve the entrenched zero-sum competition over resource allocation. Consequently, mitigating these deeply coupled socio-ecological hazards requires moving beyond static, reactive mitigation strategies toward a more holistic and predictive management paradigm. To navigate this extreme complexity, there is a critical imperative for an advanced Decision Support System (DSS) capable of seamlessly translating complex physical morpho dynamics into actionable, real-time institutional intelligence. A robust DSS must not only simulate the physical laws governing water and sediment transport but also democratize this data through accessible, API-driven interfaces to facilitate equitable governance. This fundamental necessity—bridging high-fidelity physical modelling with dynamic policy integration—serves as the conceptual blueprint for the development of RIVANA (River DNA-Analysis). Engineered specifically to function as this proactive DSS, RIVANA synthesizes empirical data and physical laws into a real-time digital twin, providing the necessary technological foundation to dissolve information asymmetry and enable evidence-based, anticipatory policymaking.

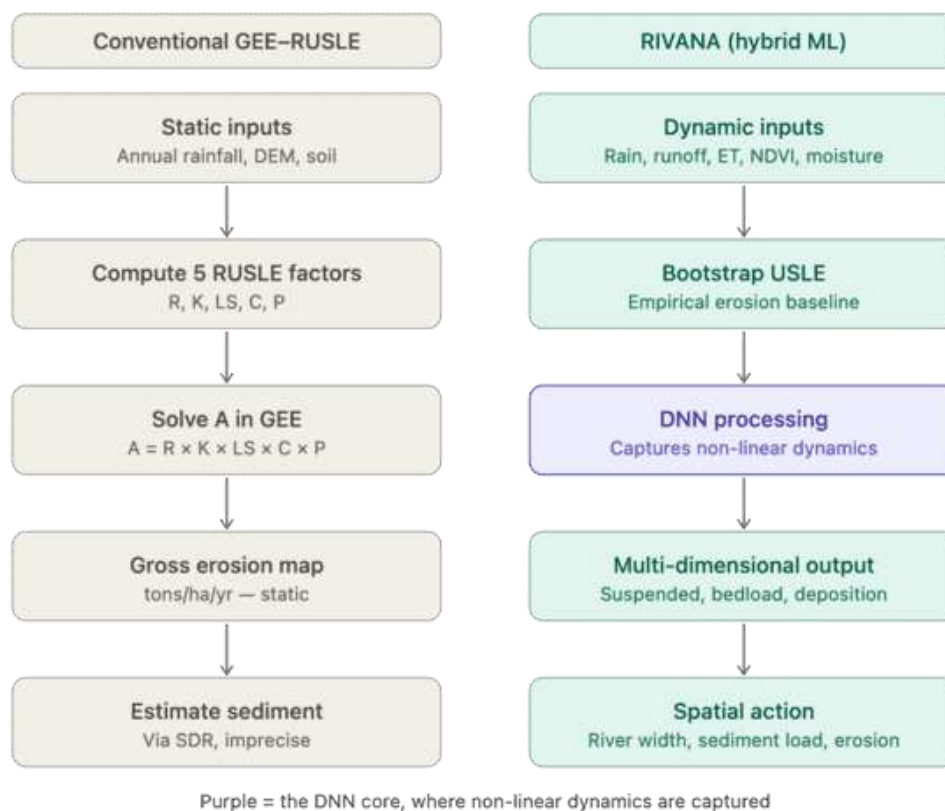


Figure 6. Workflow comparison between the conventional GEE–RUSLE approach and the RIVANA hybrid framework.

The Structural Deficiencies of Empirical Models and GEE-RUSLE

The necessity of a hybrid Physics-Informed Machine Learning (PIML) framework stems directly from the inherent design flaws of the Revised Universal Soil Loss Equation (RUSLE). The limitations of RUSLE are not merely issues of implementation, but structural constraints rooted in its empirical-statistical nature. First, RUSLE is mathematically designed to calculate only gross sheet and rill erosion; it explicitly fails to account for sediment deposition (Benavidez et al., 2018). Consequently, the equation ignores gully erosion and the complex routing of sediment before it reaches a water body, rendering it incapable of accurately quantifying the actual sediment yield at the watershed outlet. To bridge the gap between "gross erosion" and "transported sediment," conventional practices rely on the Sediment Delivery Ratio

(SDR). However, predicting SDR lacks a universally precise procedure, forcing analysts to rely on highly uncertain empirical coefficients that vary based on sediment source, texture, and watershed morphometry (Walling, 1983).

Furthermore, empirical models like USLE/RUSLE rely heavily on fragile assumptions of linearity and spatial uniformity. These models fail to adequately represent the non-linear interactions among erosion drivers, necessitating the integration of machine learning approaches to capture multi-scale soil erosion dynamics (Avand et al., 2023; Pham et al., 2025). While the integration of Google Earth Engine (GEE) with RUSLE drastically reduces computational constraints and accelerates spatial processing, it does not resolve the equation's fundamental physical blindness. Recent studies applying GEE-RUSLE successfully predicted annual erosion rates but produced static diagnostic maps (Sud et al., 2024). In the Tuntang Watershed, GEE-RUSLE identifies where soil is detached but remains blind to where it is deposited. Field reports confirm that recurrent catastrophic flooding in the lower Demak plains is physically triggered by the aggradation and silting of the river channel (Larasati et al., 2019). GEE-RUSLE alone cannot model this critical endpoint of the causal chain.

The RIVANA Paradigm: A Physics-Guided Hybrid Architecture

To transcend the parametric limitations of empirical models and interpret complex non-linear morphodynamics, RIVANA adopts a hybrid physics-ML paradigm. Purely physics-based models tend to be structurally rigid and computationally prohibitive, whereas pure ML algorithms often operate as "black boxes" that ignore established conservation laws. RIVANA synthesizes these approaches through three critical architectural blocks (Karniadakis et al., 2021): Physics-Guided Initialization (Residual Learning) while some operational frameworks refer to the use of USLE as "bootstrapping," advanced computational literature more accurately defines this mechanism as *physics-guided initialization* or *residual learning*. In this phase, the outputs of the physical model serve as foundational input features for the neural network. The ML model is subsequently trained specifically on the residual errors between the physical baseline and observational data (Jiang et al., 2025).

Dynamic Processing via Deep Neural Networks (DNN), the integration of dynamic antecedent variables—such as soil moisture, evapotranspiration, and NDVI—significantly enriches predictive capabilities. Predicting suspended sediment load (SSL) is notoriously difficult due to spatial interconnectivity and complex non-linear patterns. However, recent studies demonstrate that deep learning architectures (e.g., LSTM, DDNN) consistently outperform traditional methods in SSL prediction by capturing deep temporal dependencies (AIDahoul et al., 2021; Mohammadi-Raigani et al., 2024). Variables like soil moisture physically dictate infiltration capacity prior to storm events—a highly dynamic state that the annually-averaged RUSLE fails to capture.

RIVANA's most significant advancement is its capability to predict bedload and deposition rates, directly addressing the SDR vulnerability. However, an analytical asymmetry exists regarding model maturity. While ML prediction for suspended sediment is highly validated, predicting bedload morpho dynamics remains inherently complex.

CONCLUSION

The deployment of this hybrid framework aligns perfectly with the physical realities of the Tuntang Watershed. Geographically spanning from the upstream regulatory node of Lake Rawa Pening to the downstream alluvial plains of Demak, the basin is characterized by severe morphological vulnerability. High discharge events exacerbate riverbank erosion, creating distinct aggradation and degradation patterns that frequently force the channel into a braided morphology. Because levees in the lower basin are low and the channel is structurally compromised by siltation, seasonal heavy rainfall invariably results in catastrophic overtopping. By providing actionable, mathematically constrained data on *where* in the channel aggradation is actively occurring, RIVANA delivers concrete, proactive value for regional disaster mitigation.

To maintain analytical rigor, it is critical to acknowledge the limitations inherent within the RIVANA framework: (1) Data Dependency: The accuracy of both the baseline physics models and the neural network predictions is inextricably linked to the quality and availability of input data. In tropical watersheds with sparse physical sediment-gauging stations, relying solely on historical rainfall records and satellite telemetry presents a significant constraint. (2) Omission of Specific Physical Processes: Despite its hybrid nature, the framework inherits certain limitations in capturing deep, process-based erosion mechanics. The current architecture struggles to autonomously model phenomena such as deep gully formation or mass wasting (landslides), which require integration with highly specific slope-stability algorithms. (3) The Interpretability Deficit: While Artificial Neural Networks (ANNs) achieve superior predictive accuracy, they inherently suffer from a "black box" operational nature. This lack of interpretability can fail to provide reliable measures of predictive uncertainty (Mohammadi-Raigani et al., 2024). In real-world governance, if a model dictates critical infrastructure interventions in Demak, the decision-making rationale must be mathematically transparent. Consequently, future iterations of RIVANA must integrate explainable AI tools or Bayesian Uncertainty Quantification.

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